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Discussion Paper

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NLS Discussion Papers

The Effects of Unemployment Compensation on the Employment of Youths

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September 1989

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FINAL REPORT
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THE EFFECTS OF UNEMPLOYMENT COMPENSATION ON THE UNEMPLOYMENT OF YOUTHS

by

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September 1989

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Executive Summary

Objectives

This report examines the role of unemployment insurance (UI) policies on the amount of unemployment that youths experience between jobs. Specifically, the analysis focuses on determining how the weekly benefit amounts and the weeks of eligibility offered by UI programs influence three aspects of nonemployment activities: the total length of time spent in nonemployment; the fraction of this time reported as unemployment; and the likelihood that an individual collects UI during a nonemployment episode.

En route to this primary objective, we pursue two intermediate goals concerned with developing a picture of youths' participation in the labor market and utilization of UI programs exploiting the rich source of data provided by the Youth Cohort of National Longitudinal Survey (YNLS). The first of these goals involves the computation of a comprehensive summary of the weekly work and earnings experiences of youths, and the second consists of assessing the extent to which youths are eligible for UI and the degree to which they draw on UI entitlements. The aim is to identify two sets of patterns: those describing differences across demographic characteristics; and those capturing changes over the period 1979–1984 covered by the data.

Methodology

The analysis constructs a data set that links individuals' unemployment experiences to dependable measures of their UI eligibility, benefits and use. The YNLS offers information on a random sample of youths with detailed histories of each person's labor-market statuses, along with considerable data on profiles of weekly earnings, on episodes of both employment and nonemployment, and on the division of nonemployment time between out-of-the-labor-force and unemployment classifications. In conjunction with supplementary data on State of residency and UI-program rules of that State, the analysis infers the weekly benefit amount and the weeks of UI eligibility available to each person at the time of every job separation; and it further combines this information with the characteristics associated with the resulting nonemployment episode. The constructed data set is unique in that no other source relates CPS-type measures of unemployment to the full complement of UI entitlements (i.e. to both the weekly benefit amount and to weeks of eligibility) and to UI collection.

To assess the influence of UI policies on the distribution of unemployment durations that occur upon leaving jobs, this study develops an econometric model that jointly determines the effects of UI on three aspects of behavior which in combination characterise the nonemployment activities of individuals. One component of the model describes the role of UI programs on the lengths of nonemployment spells. A second evaluates the effects of UI

on the classification of these spells as unemployment. Finally, to account for distinctions between UI recipients and non-recipients, a third component of the model analyzes whether the generosity of UI programs influences the likelihood that individuals collect UI benefits. In specifying these components, this study accounts for all the dimensions of UI benefits and allows these benefits to affect unemployment in a nonuniform manner varying according duration length. Further, the analysis takes great care to avoid biases in estimating responses to UI entitlements by ensuring that variation in benefits reflect differences in the generosity of UI programs rather than movements along UI schedules.

Findings

For men, the empirical results presented in this study indicate that an individual who collects UI typically experiences a longer spell of nonemployment, at least up to the exhaustion of UI benefits, and reports a larger fraction of this spell as unemployment than a nonrecipient. In total, UI recipients report more weeks of unemployment before returing to jobs.

Regarding the influence of UI entitlements on the experiences of men, these benefits alter individuals' activities through several routes. Concerning the effect of a rise in the weekly benefit amount paid by a program, the results show slight increases in recipiency and in the fraction of a nonemployment spell listed as unemployment; but this rise in weekly benefits has essentially no effect on either the length of nonemployment spells or on the number of weeks of unemployment, irrespective of whether one considers the population at large or only the population of UI recipients.

Turning to the effects of an increase in the weeks of eligibility offered by a program, this policy shift induces only a relatively minor rise in the likelihood of recipiency, as is the case for an increase in weekly benefit amounts. However, in sharp contrast to the effects of weekly benefits, an extension of weeks of UI eligibility lengthens both nonemployment spells and the amount of unemployment that occurs between jobs both for UI recipients and for the population at large. This extension does not influence short durations of either nonemployment or unemployment, but it leads to an expansion of the longer durations with the highest durations being stretched out the most. In particular, the findings indicate that an extention of weeks of eligibility from 26 to 39 generates only about a 1 week lengthening of unemployment duration for the median individual, but unemployment lengthens by as much as 8 weeks for those persons experiencing the longer durations.

The findings summarized above for young men also apply for young women with only two exceptions. First, while female UI recipients experience more unemployment than nonrecipients at least up to the point of benefit exhaustion, there is some ambiguity as to whether

a similar relationship exists for women when comparing lengths of nonemployment spells. Second, the weekly benefit amount is not a factor at all in influencing women's experiences. In contrast to men, changes in weekly benefits have no effect on the fraction of a nonemployment spell reported as unemployment, nor do they affect the likelihood that a women collects UI benefits. Whereas total UI benefits serve as the primary measure of UI entitlements determining UI recipiency status for men, the results for women indicate that only weeks of eligibility matter. Other than these two relatively minor exceptions, the influences of UI policies on women's experiences between jobs in nonemployment and in unemployment follow the same pattern as those outlined above for men, although the magnitudes of the various effects differ.

Implications

The findings of this report suggest several implications concerning the role of UI policies on the amount of unemployment. At the most basic level, the results indicate that features of UI programs that change the size of weekly benefit amounts are not likely to affect unemployment, whereas features that alter the amount of weeks of eligibility are likely to shift unemployment for those individuals who experience the longer durations. Thus, changes in the maximum level of weekly benefits paid by a program can be expected to have no effect on unemployment. In contrast, the introduction of extended benefit programs can be expected to lead to greater unemployment with a more uneven distribution of experiences across nonemployed persons.

At a more subtle level, these implications highlight the importance of eligibility qualifications in UI programs. A casual comparison of UI regimes across states reveals that those programs paying higher benefits also apply more stringent qualification requirements. Such programs in effect offer higher weekly benefit amounts to those persons who qualify and at the same time assign zero weeks to eligibility to a greater fraction of the nonemployed population. Consequently, these programs are likely to induce less unemployment according to the findings of this report because the higher weekly benefit amount paid by a program yields no change and the lowering to weeks of eligibility reduces the amount of unemployment.

1. Introduction

Over the past 20 years there has been a steady flow of empirical research on evaluating the effects of unemployment insurance (UI) programs on the unemployment activities of various demographic groups. Regardless of the group considered, assessing the full impact of these programs requires empirical knowledge of the way in which UI policies influence a variety of labor-market decisions. Most obvious, one needs to know how changes in a UI system alter the unemployment duration of recipients of UI benefits. In addition, one needs to determine whether such changes induce nonworking individuals to become UI recipients. Considering more indirect effects, an analyst also requires information concerning the potential responses of working individuals to policy changes in adjusting their employment activities to collect future UI benefits. Finally, if program changes involve alterations in financing features, one needs some determination of the likelihood that firms alter their hiring and separation behavior. Existing research examines aspects of each of these possible routes through which UI can influence unemployment, but available studies tend to consider effects in isolation due to data limitations or methodological problems. Incompatibilities across studies make it very difficult to integrate results for the purpose of developing reliable estimates of comprehensive effects of UI policies that account for combinations of the factors noted above. This paper presents an empirical analysis that provides estimates of such effects. The analysis exploits a new data source that permits one to overcome many of the shortcomings inherent in other sources, and it develops a flexible econometric framework for assessing the role of UI-system features on the nonemployment experiences of individuals accounting for both their unemployment activities and participation in UI programs.

The central empirical question investigated in this analysis concerns the influence of UI policies on the amount of unemployment that individuals experience between jobs, where the concept of unemployment of interest corresponds to a CPS type measure of the sort most commonly cited in national statistics rather than weeks of UI collection which is a popular choice for other research on this topic. To study the effects of UI entitlements on how much unemployment occurs during spells of nonemployment, one needs to examine the influence of these entitlements on both the length of nonemployment spells and the division of these spells

between unemployment and out-of-the-labor force (OLF) activities. One often encounters the argument that the distinction between being unemployed and OLF is an arbitrary choice for many people when they are not working. Eligibility to receive UI benefits during this time along with the levels of these benefits are potentially important factors in explaining a person's decision to report himself or herself as unemployed instead of as OLF during an episode of nonemployment. The current body of empirical research provides only indirect evidence at best to infer the influence of UI on the distinction between unemployed and OLF; in fact, most of this work does not even recognize OLF as a possible status in the labor market.

Data limitations have been a major obstacle in analyzing the relationships linking UI and unemployment experiences, regardless of the demographic group considered. A study of the full effects of UI makes substantial demands of any sample used in the empirical work. A sample must include sufficient information to infer the potential UI benefits available to individuals over an extended time horizon, to determine the utilization of these benefits over this horizon, and to relate these items to the individuals' unemployment experiences during the relevant time frame. Further, the sample requires a random composition in order to draw inferences from its results about the effects of UI policies on segments of the U.S. population. Data sources analyzed in the existing literature do not meet these demands. Past research either uses program data, which offers accurate information on UI entitlements only for samples of UI recipients, or uses survey data, which provides a random sample with sparse information to infer individuals' UI benefits, eligibility, and utilization. Program data permit one to analyze the unemployment durations of UI recipients, but only if one is interested in that concept of unemployment measured as time spent collecting UI compensation; these data do not allow for an analysis of the effects of UI policies on CPS measures of unemployment. Further, program data do not provide a basis for evaluating the impact of policies on shifting individuals to recipiency status. Survey data, on the other hand, often lack sufficient information to include key benefit variables in specifications and to create reliable proxies for those included. The shortage of information in survey data also commonly forces the imposition of stationarity assumptions in statistical models, which

results in specifications known to be grossly inconsistent with the facts.

This paper develops and analyzes a new data set based on the Youth Cohort of the National Longitudinal Survey (YNLS), which constitutes an unparalleled source for studying the influence of UI programs on youths' labor market experiences. The YNLS offers a random sample of youths with detailed histories of each person's labor market statuses over a period covering the years 1978 through mid- 1985, with considerable data available on earnings and on episodes of both employment and nonemployment. In conjunction with supplementary data on State of residency and UI program rules of that State, the YNLS provides sufficient information to construct an accurate assessment of an individual's UI eligibility, benefits and utilization. Exploiting the unique opportunity offered by the YNLS to link the unemployment histories of a random sample of individuals to dependable measures of their UI eligibility, this analysis explores the importance of UI benefits on the unemployment durations of young people.

En route to examining this topic, this paper develops a comprehensive picture of youth's involvement in UI programs and their nonemployment experiences. The analysis assesses the extent to which youths are eligible for UI and the degree to which they draw on UI entitlements. Further, it links this information to a variety of measures of time spent in nonemployment activities, including time in insured and total unemployment. In addition to offering insights into the connections between UI and unemployment, the analysis presented here furnishes a natural setting for integrating and evaluating many findings in the literature.

To develop a comprehensive picture of the influence of UI policies on the distribution of unemployment durations that occur upon leaving jobs, this paper proposes an econometric model that jointly determines the effects of UI on three aspects of behavior which in combination characterize the nonemployment activities of individuals. One component of the model describes the role of UI programs on the lengths of nonemployment spells. A second assesses the effects of UI on the classification of these spells as unemployment. Finally, to account for distinctions between UI recipients and non-recipients, a third component of the model analyzes whether the generosity of UI programs influences the likelihood that individuals collect UI benefits. In specifying these components, this study accounts for all the

dimensions of UI benefits and incorporates controls for the tax-rate features faced by firms in financing programs. Further, the analysis takes great care to avoid biases in estimating responses to UI entitlements by ensuring that variation in benefits reflect differences in the generosity of UI programs rather than differences in workers' attributes which also determine benefits.

The remainder of this report consists of ten sections. Section 2 outlines the advantages of the YNLS over other sources for constructing a data set that integrates UI entitlements and unemployment for a random sample of individuals. Section 3 characterizes the earnings and employment experiences of youths using the weekly work histories provided by the YNLS. Section 4 provides a detailed account of youths' eligibility for and utilization of UI during the first half of the 1980's decade. Section 5 presents an econometric framework for analyzing the effects of UI on unemployment, and Section 6 tailors this framework to investigate the problem of whether the generosity of UI programs influences the amount of unemployment youths experience between jobs. As a first step in answering this question, Section 7 investigates the effects of UI programs on the lengths of spells in nonemployment. Section 8 proceeds to the next step and examines the relationships between UI entitlements and the fraction of nonemployment time classified as unemployment. Section 9 explores the empirical link between UI recipiency and UI benefits. Section 10 combines the findings to determine the comprehensive effects of UI policies on the duration of unemployment that occurs after job separations. Finally, Section 11 summarizes the results.

2. Linking UI Entitlements and Unemployment Experiences

Data limitations have severely curtailed our ability to formulate a comprehensive description of the links between unemployment, UI eligibility, and UI utilization. The main obstacles stem from an incapacity using current data sources to reliably match potential UI benefits and the collection of these benefits to measures of unemployment. Such a match requires sufficient information not only to distinguish between the amounts of insured and uninsured unemployment experienced by an individual over an extended time horizon, but also to infer the individual's UI entitlements over this horizon. The inadequacies of data sources to provide this level of information have forced previous research either to focus on narrow aspects of the relationship between unemployment and UI programs or to make substantial compromises in accounting for data shortcomings. These compromises often take the form of heroic assumptions that permit the creation of proxies for missing information, and they also commonly involve the introduction of restrictive statistical structures to avoid the need for detailed knowledge. Given the deficiencies of data sources used in previous work, there has been no opportunity to provide an assessment of the degree to which these compromises have clouded our understanding of the empirical relationships linking UI eligibility, UI participation and unemployment experiences. The availability of the YNLS provides an opportunity to begin such an assessment.

2.1 *Data Requirements to Impute UI Eligibility and Benefits*

A considerable amount of information is needed to determine whether an individual is eligible to receive UI compensation and the amount of benefits to which he or she is entitled. The specific rules and regulations determining eligibility, weekly benefit amounts and potential duration vary substantially across states and are characterized by complex relationships between an individual's earnings history, benefit schedules and qualification requirements. One essentially requires a complete time series of weekly earnings to obtain accurate measures of the UI benefits individuals are entitled to receive; the rules determining eligibility in almost every state depend not only on the amount of income, but also on the pattern of wages over the relevant time period.

The entitlement variables associated with UI programs consist of an assigned weekly ben-

efit amount (*WBA*) and the number of weeks of eligibility during which benefits are available (*WE*). An individual must meet certain criteria to qualify for benefits and then satisfy a set of qualification requirements on a week by week basis. While the weekly qualification tests are not unimportant, the program features of central importance for this analysis are the set of eligibility criteria. These conditions determine whether an individual is entitled to any benefits as well as the amount of benefits available during a fifty-two week period initiated with the filing of a UI claim, termed the "benefit year."

While there is a large amount of diversity among States in the exact rules used to determine entitlements, every State applies two types of eligibility criteria. The first concerns the reason for separation from the most recent employer. All States have disqualification provisions for leaving work without good cause, discharge for misconduct and unemployment resulting from direct involvement in a labor dispute. The second eligibility criterion requires a worker to have an employment history that demonstrates a permanent attachment to the labor force. The evidence for such an attachment consists of a minimum level of earnings and/or a minimum number of weeks of work in covered employment during a recent fifty-two week period, termed the "base period."

All States use some combination of total earnings received in the base period (*BPE*), highest earnings in any quarter of the base period (*HQE*), and total weeks of work during the base period (*WW*) to establish an individuals eligibility to receive UI payments. Approximately half of the States require a worker to have a minimum *HQE* along with *BPE* greater than some multiple (usually 1.25 or 1.5) of *HQE* to become eligible for benefits. Another one-fourth of the State express their eligibility requirements in terms of a minimum level of *BPE*, and half of these States add a requirement of wages in more than one calendar quarter. The remainder of the States determine eligibility based upon a required number of weeks of work with wages greater than some nominal amount. Whether explicit or implicit, all but five States require wages in more than one calendar quarter for an individual to be judged eligible for UI payments.

Once deemed eligible, an individual's *WBA* is determined as a fraction of his or her "usual" earnings in covered employment up to some maximum level such that approximately

half of the usual weekly wage is replaced by UI payments. States use three methods to calculate a person's *WBA*. The most common method defines usual earnings as *HQE* with *WBA* typically equal to 1/25 of *HQE*. A second approach defines the usual wage as average weekly earnings (*AWE*) over the base period (i.e., $AWE = BPE/WW$). Among the ten States using this procedure the *WBA* ranges from 1/2 to 2/3 of *AWE*. Finally, the third regime sets the *WBA* equal to approximately 1.5 percent of *BPE*, which implicitly defines *BPE* as the appropriate measure of usual earnings.

States apply two basic approaches for determining the number of weeks of benefits (*WE*) available to qualified individuals. The first approach, adopted by about ten States, provides the same number of weeks of benefits to every individual who is eligible for UI payments. All but a few of these uniform duration States provide everyone with twenty-six weeks of benefits. The second approach determines *WE* as a function of an individual's work experiences in the base period by one of three methods that use information on *BPE*, *HQE* and *WW*. The most prevalent method calculates the total amount of benefits available (*TBA*) to an individual over the benefit year as a fraction (usually 1/3) of *BPE* and then calculates *WE* by the ratio of TBA/WBA up to a maximum number of weeks. Another common method assigns *WE* as a fraction ranging from 1/2 to 4/5 of *WW* in the base period, again up to some maximum. The third scheme determines *WE* by using a schedule based on the ratio of *BPE* to *HQE*. Under this regime, an individual with a ratio above 3.5 is assigned the maximum number of weeks, people with a ratio close to 1.5 are allotted the minimum number of weeks, and individuals with a ratio between these two extremes are given an intermediate number of weeks.

2.2 *Data Sources Used in the Previous Literature*

There are principally two types of data analyzed in existing studies to examine the issues of UI eligibility and utilization. First, there are data available from State administration offices of UI programs, such as that provided by the Continuous Wage Benefit History (CWBH).[1] While these program data sets offer very reliable information on the amount and potential duration of UI compensation, the individuals making up these samples are observed

[1] Studies using such data sources include Newton and Rosen (1979), Classen (1979), and Moffitt (1985).

only as long as they are actually collecting benefits. Consequently, these data sets include information on only a very select group of the nonworking population (i.e. UI recipients).

Second, there are data from various representative surveys of individuals such as the CPS, the Panel Study of Income Dynamics (PSID), and the earlier National Longitudinal Surveys (NLS).[2] In contrast to the first type of data, these survey data contain insufficient information to impute individuals' potential UI compensation without relying on assumptions that are not credible. Previous studies (e.g. Clark and Summers (1982a), Topel (1985), and Blank and Card (1988)) have attempted to infer a person's eligibility and available benefits by treating an out-of-work individual's previous annual labor income as the appropriate measure of his or her earnings history. Further, one often cannot distinguish between insured and uninsured unemployment in these surveys and at best these sources provide data on accumulated unemployment during a year or on single episodes of unemployment over a relatively short time horizon with some spells interrupted in progress.

2.3 *Features of the YNLS*

The YNLS classifies among the second type of data listed above, but it supplies an incomparable source of information on the unemployment and employment activities of youths that enables one to overcome many of the problems encountered with the data sets used in past work. The YNLS includes a nationally representative sample of youths with comprehensive histories on each person's labor-market statuses and earnings over a period covering the years 1978 through mid-1985. In conjunction with supplementary data on State of residency and the UI benefit rules of that State, the YNLS provides sufficient employment information to infer an individual's UI eligibility and available benefits during times of unemployment. In addition, these data contain comprehensive information on the receipt of UI benefits, providing reliable calendar year information on the total number of weeks a youth received UI payments, the average weekly benefit amount over the year and the months in which benefits were received. When combined, these data permit one to construct a reasonably accurate picture integrating UI entitlements, the utilization of these entitlements, and the

[2] Studies using such data sources include Ehrenberg and Oaxaca (1976), Clark and Summers (1979, 1982a) and Katz (1986).

labor market activities of individuals.

The development of this picture initially requires the construction of complete work histories of individuals, not only dating their periods of employment, nonemployment and unemployment, but also identifying the precise time pattern of their weekly earnings. This level of detail is needed to infer UI benefits and to determine the availability of these benefits during episodes when individuals do not work. The task of describing the earnings and employment experiences of youths is the topic of Section 3, which immediately follows the current discussion.

Using this information on work histories to impute UI benefits, Section 4 examines the extent to which young workers are eligible for UI benefits along with the degree to which they draw on available compensation. Knowledge of youths' eligibility and utilization of UI is an important ingredient in assessing the role of UI programs on their labor market activities. To take advantage of the richness of the information provided by the YNLS on the collection of UI compensation, the analysis focuses on calendar years as the periods of observation.

The later sections exploit the data set characterized in Sections 3 and 4 to examine the influence of UI policy on the nonemployment experiences of youths. The particular problem of concern in this analysis is to determine whether the generosity of UI programs affects the amount of unemployment that occurs between jobs. Such an empirical analysis cannot be done without the opportunity provided by the YNLS to construct a data set that links UI entitlements, UI collection and labor market activities.

While the YNLS offers this unique opportunity, there are three shortcomings of the YNLS relevant to this analysis. First, data are not provided on the lengths of unemployment spells, but only on the number of weeks that an individual reports himself or herself as being unemployed during a contiguous sequence of weeks in which the youth does not work. This lack of information on the timing of unemployment spells rules out the possibility of applying familiar statistical models of duration analysis and has lead us to focus on predicting the effects of UI programs on the total number of weeks a youth reports himself or herself as unemployed during a nonemployment episode.

A second limitation of the YNLS arises because survey respondents were not asked detailed questions about extraneous jobs. Specifically, wage information is missing for jobs that were not the main job held at the date of the interview, were not part of a government training program, and were held for less than nine weeks or required less than twenty hours of work per week. To obtain uninterrupted time series of weekly earnings for as many people as possible, we impute a wage rate for those individuals with missing wage information even though the earnings from these small jobs account for a negligible fraction of total labor income. This imputation procedure utilizes wage data available in preceding and subsequent interviews as well as earnings on other jobs held during the current interview year. Appendix A contains a description of the procedures used to impute wages rates for those jobs with missing information.

Third, while the YNLS contains more comprehensive information on the receipt of UI benefits than are available in other data sources, these data preclude a detailed analysis of UI utilization within single nonemployment episodes. Specifically, the YNLS provides reliable calendar year information on the total number of weeks a youth received UI payments, the average weekly benefit amount over the year and the months in which benefits were received. However, this annual information is insufficient to determine what occurs within each nonemployment spell, unless an individual happens to experience only one nonemployment spell that starts and ends within the year. We can infer whether UI receipt takes place within spells, but not how much.

3. A Description of the Earnings and Employment Experiences of Youths

The imputation of UI benefits requires comprehensive earnings information on individuals during a 12-month horizon (termed a base period). Remarkably little is known about the patterns and volatility of labor market activities over such horizons. Current knowledge of these activities in the case of youths rests primarily on information from the Current Population Survey, the National Longitudinal Surveys of Young Men and of Young Women, and the National Longitudinal Survey of 1972 High School Seniors. These data essentially depict the earnings and employment activities of individuals either in the context of a short sequence of survey weeks or over a previous calendar year at a level of detail indicating the number of weeks worked, usual hours worked per week, and annual earnings. While such information conveys the broad outlines of annual experiences, it fails to capture much of the volatility that occurs within a year.

The YNLS provides a source for constructing a weekly history of both earnings and hours of work which one can use to summarize the patterns of these quantities over annual periods. The following discussion describes these work histories at decreasing levels of aggregation. In summarizing earnings experiences the analysis begins with annual measures, then considers characteristics of weekly earnings over the year, and finally examines the patterns of hourly earnings. The discussion next turns to the topic of employment experiences. This analysis begins by summarizing information about weeks worked and jobs held within a year, and it then takes up the topic of annual and weekly measures of hours worked.

3.1 *Sample Compositions and Descriptive Statistics*

The following discussion considers a variety of variables to characterize both the earnings and the employment experiences of youths within annual horizons, with the focus directed towards describing how these variables vary across and within age-education groups and over time. The 12-month horizons considered in this analysis correspond to the 6 calendar years 1979–1984. The samples used to describe each variable consist of all the observations on individuals in the YNLS for which data are available for the year considered.

The use of all available data means that different sample compositions are exploited

depending on the particular variable and year analyzed. Appendix A describes these sample compositions in detail and reports the sample sizes associated with each composition for the years 1979–84 (i.e. see Section A.5 and Tables A.1). The least stringent sample selection criteria incorporate all individuals who are age 18 or more in March of the calendar year, not in the military and not in school at any time during the year, and with education of grade 8 or more. The more stringent criteria require individuals to work some time during the year and for there to be non-missing data for these individuals on a wide range of variables needed to infer earnings and employment experiences, with the most demanding data requirement involving the availability of wage rates for all jobs held during the year – recall that the YNLS does not supply wage information for intermittent jobs. In all, the analysis of this section relies on twelve distinct sample compositions to construct the various descriptions of youths' labor-market experiences.

There are two dimensions of interest for describing how the various measures of earnings and work activities vary among youths: the first involves a comparison across different education and age groups; and the second focuses on the time path of these measures. This analysis considers both of these dimensions. It does so by decomposing each measure into age-education and time effects using a simple regression framework.

In particular, let the variable y_{it} denote an observation associated with an earnings or hours-of-work measure for the i^{th} individual in year t. Consider the regression equation

$$y_{it} = \sum_{j=1}^{T} \theta_j \, d_{1j} + \sum_{k=1}^{K} \gamma_k \, d_{2k} + \text{ error,} \tag{3.1}$$

where $d_{1j} = 1$ if $t = j$ and $= 0$ otherwise, and $d_{2k} = 1$ if individual i is a member of age-education group k and $= 0$ otherwise; in other words, the d_{1j}'s are time dummies and the d_{2k}'s are age-education dummies. Impose the identification condition $\sum_{j=1}^{T} \theta_j = 0$, in which case the coefficient γ_k represents the average of y associated with age-education group k over the period 1 to $T (k = 1, \ldots, K)$, and the θ_j's represent the common deviation experienced by all groups in year $j \, (j = 1, \ldots T)$.

In the following empirical work the periods $1 \ldots T$ refer to the calendar years 1979, ..., 1984. The age-education categories considered below are: (1) ages 18–19, 20–22, 23–24, 25–27 for grades 8–11; (2) ages 18–19, 20–22, 23–24, 25–27 for grade 12; (3) ages 20–22,

23–24, 25–27 for grades 13–15; and (4) ages 23-24, 25–27 for grades 16 and above (i.e. 16+). The term grade here refers to the highest year of education completed by an individual. Tables A.1–M and A.1–W in Appendix A list respectively for men and women the sample sizes associated with these various age-education categories for each of the years and the alternative sample compositions.

3.2 *Measures of Annual Earnings*

Information from the YNLS permits the construction of two variables measuring the earnings of individuals over the period of a calendar year. These quantities are:

$$\text{ARE} = \text{annual reported earnings;}$$

$$\text{ACE} = \text{annual computed earnings.}$$

The first variable corresponds to a CPS-type measure of annual earnings, which is a data item directly collected by the YNLS for each calendar year. One calculates the second variable by summing the weekly earnings received on all jobs held in those weeks making up the calendar year. The construction of ACE requires use of all the wage and employment history information provided by the YNLS, which involves a considerable amount of detail. Appendix A (Sections A.2, A.3 and A.5) describes the steps followed to create values of both ARE and ACE, along with the sample compositions associated with each variable.

Tables 3.1–M and 3.1–W present summary statistics describing the variation of these earnings measures across and within the various age-education categories and over time. The designator "M" attached to the numbering of a table indicates that the results refer to men, while the designator "W" signifies that the statistics refer to women. Each column of a table presents results for a variable listed at the top of the column. Moving down a column, three numbers appear in each box: the top number is the estimate of the coefficient γ_k from regression equation (3.1), with k identifying the age-education group listed along the corresponding row at the far left of the table and with the variable listed at the top of the column taken as the dependent variable y in the regression; and the two numbers reported below this estimate of γ_k represent the lower and the upper quartiles associated with all observations falling into the designated demographic group in all years. Thus, the top number gives the average for an age-education group, and the two lower numbers

describe the dispersion within the group. The six numbers reported in the bottom rows of each column are the estimates of the θ_j's from regression (3.1), which capture the period effects occurring in each of the calendar years.

Tables 3.1–M and 3.1–W report statistics describing the variation in the annual earnings measures ARE and ACE. The second column of these tables, with the variable ARE_ listed at the top, presents results computed for the variable ARE using a sample composition which matches that used in constructing ACE. Because the calculation of ACE requires nonmissing data on a wide range of variables in the YNLS, the sample available for summarizing the properties of ACE is smaller than that available for characterizing ARE. The ACE sample excludes individuals who hold intermittent jobs at any time during the year – because wage data are unavailable for these jobs – so the earnings data for these persons do not go into the description of ACE. A comparison of the results in the first and second columns shows that the average values of ARE are higher in the sample used to construct ACE, which is consistent with the view that annual earnings are lower for individuals who hold intermittent jobs.

Three patterns emerge from the results in Tables 3.1. First, average annual earnings increase with age and education. Second, dispersion within demographic categories typically increases with age and education. Finally, average earnings generally declined over the period 1979–1984.

3.3 *Reliability of Earnings Measures*

In carrying out the empirical work on the effects of UI discussed in the later sections of this report, we infer UI entitlements of individuals using weekly data on earnings. This is the same sort of information that goes into the construction of ACE. Thus, assessing the accuracy of ACE as a measure of annual earnings provides some guidance as to the reliability of our imputations for UI benefits done below. The sample composition used below to impute UI benefits is much less restrictive than the ACE sample composition considered here because missing wage information is assigned where possible in constructing the samples containing imputed UI information to avoid deleting individuals who hold intermittent jobs in covered employment. (See Appendices A and B for further discussion of this issue.) In any case,

TABLE 3.1-M
Summary Statistics for Measures of Annual Earnings*
(1984 $)

VARIABLE		ARE ($1000)			ARE_ ($1,000)			ACE ($1,000)		
EDUC.	AGE	Mean	25%	75%	Mean	25%	75%	Mean	25%	75%
8+	18-19	7.6	2.5	10.7	8.7	3.8	11.5	8.9	4.5	12.1
	20-22	10.2	4.0	14.0	11.2	5.4	14.6	11.6	5.9	15.2
	23-24	11.7	4.8	15.6	12.3	5.3	16.0	13.1	7.4	15.9
	25-27	13.4	4.2	15.8	14.3	5.0	16.7	14.8	5.8	18.1
12	18-19	10.0	5.1	13.8	10.5	5.8	14.1	11.2	6.8	14.3
	20-22	13.2	7.3	17.4	13.8	8.3	18.2	14.4	8.8	18.6
	23-24	16.5	9.7	20.8	17.1	10.3	21.1	17.7	10.8	20.8
	25-27	18.1	10.4	24.0	19.1	12.1	24.0	19.0	12.4	22.6
13+	20-22	14.4	8.5	18.3	14.7	9.4	18.8	15.1	10.1	19.3
	23-24	17.3	10.3	21.9	18.7	12.0	23.0	18.9	12.0	23.5
	25-27	18.7	10.8	23.5	19.2	10.6	23.2	19.0	11.0	24.4
16+	23-24	19.4	11.8	25.0	20.6	14.1	26.0	21.1	13.6	26.1
	25-27	23.8	14.6	30.3	25.4	16.0	31.2	25.7	16.5	30.5

<u>Year Effects</u>		ARE		ARE_		ACE	
79	80	2.0	0.5	2.3	0.9	3.2	1.0
81	82	0.2	-0.7	0.1	-0.7	-0.1	-0.9
83	84	-1.2	-0.8	-1.6	-1.0	-1.9	-1.3

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.1-W
Summary Statistics for Measures of Annual Earnings*
(1984 $)

VARIABLE EDUC.	AGE	ARE ($1000) mean	ARE ($1000) 25%	ARE ($1000) 75%	ARE_ ($1,000) mean	ARE_ ($1,000) 25%	ARE_ ($1,000) 75%	ACE ($1,000) mean	ACE ($1,000) 25%	ACE ($1,000) 75%
8+	18-19	3.9	1.0	5.7	4.5	1.1	7.1	4.7	1.2	7.4
	20-22	5.0	1.3	7.8	5.4	1.4	8.3	5.9	1.8	9.0
	23-24	6.3	1.6	9.6	6.8	2.0	9.9	6.9	2.3	10.0
	25-27	5.6	1.3	9.3	5.8	1.4	9.7	6.2	1.5	9.5
12	18-19	6.9	2.9	10.0	7.4	3.7	10.3	7.8	3.8	10.7
	20-22	8.1	3.6	11.4	8.8	4.8	11.8	9.0	5.0	12.1
	23-24	8.7	3.6	12.1	9.2	4.3	12.5	9.5	4.8	12.7
	25-27	9.5	4.0	13.5	10.0	5.0	13.7	10.2	4.8	13.8
13+	20-22	9.7	5.4	12.9	10.3	6.6	13.6	10.7	6.8	14.0
	23-24	10.8	6.2	15.0	11.0	6.7	15.0	11.6	6.3	15.2
	25-27	11.4	6.9	15.0	11.8	7.4	15.5	12.1	6.9	15.9
16+	23-24	13.6	9.2	17.0	14.4	9.6	17.9	14.5	9.6	18.1
	25-27	14.9	9.3	19.2	15.4	9.7	20.0	15.2	8.9	20.2
Year Effects										
79	80		0.4	0.2		0.7	0.4		0.8	0.6
81	82		0.0	-0.4		-0.1	-0.6		-0.0	-0.6
83	84		-0.3	-0.0		-0.3	-0.1		-0.5	-0.3

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

while the sample composition exploited in the current analysis of ACE differs somewhat from that used in the subsequent study of UI benefits, evaluating the degree of measurement error contaminating ACE for the samples considered here provides a valuable source of evidence for judging the reasonableness of our subsequent imputations of UI entitlements.

A comparison of the variables ARE and ACE offers a simple approach for assessing the relative accuracies for these quantities as measures of annual earnings. Inspection of columns 2 and 3 of Tables 3.1 reveals a great deal of agreement in the averages and the dispersions implied by these two variables for similar sample compositions.

A more sophisticated approach for detecting the extent of measurement error in the variables ARE and ACE involves the implementation of a multiple indicator model. Suppose that both ARE and ACE are imperfect indicators of "true annual earnings", denoted by the variable TE. Following a classical errors-in-the-variable framework, assume that the two observed earnings quantities ARE and ACE relate to the unobserved quantity TE via the relationships:

$$\begin{aligned} \ell n\,\mathrm{ARE} &= b + lnTE + \epsilon_r \\ \ell n\,\mathrm{ACE} &= -b + lnTE + \epsilon_c, \end{aligned} \tag{3.2}$$

where the coefficient b is an intercept, and ϵ_r and ϵ_c are mutually independent measurement error terms which are distributed independently of the natural log of true earnings and which possess zero means and variances equal to σ_r^2 and σ_c^2 respectively. Accordingly, the total variances of the two observed earnings variables decompose as: $\sigma^2_{\mathrm{ARE}} = \sigma^2_{TE} + \sigma^2_r$ and $\sigma^2_{\mathrm{ACE}} = \sigma^2_{TE} + \sigma^2_c$, where the symbols σ^2_{ARE}, σ^2_{ACE}, and σ^2_{TE} denote the variances of the quantities $\ell n\,\mathrm{ARE}$, $\ell n\,\mathrm{ACE}$, and $\ell n\,TE$ respectively. The parameters σ_r^2 and σ_c^2 determine the dispersion of measurement error in the two annual earnings variables, with a larger σ_r^2 (σ_c^2) signifying more noise in ARE (ACE). The expected values of the various earnings quantities relate to one another according to the relation $E(\ell nTE) = [E(\ell n\,\mathrm{ARE}) + E(\ell n\,\mathrm{ACE})]/2$.

Use of a single cross-section of data on ARE and ACE – i.e. given a sample of observations on ARE_i and ACE_i for individuals $i = 1, \ldots, N$ for a specific calendar year – provides sufficient information to estimate the parameters σ_r^2, σ_c^2, σ^2_{TE}, b and $E(\ell nTE)$. In particular, one can estimate the first and second moments of $\ell n\,\mathrm{ARE}$ and $\ell n\,\mathrm{ACE}$ from the cross-section

data and then develop estimates of structural parameters exploiting the relationships:

$$\sigma_r^2 = \sigma_{\text{ARE}}^2 - \text{cov}\,(\ell n\,\text{ARE},\ \ell n\,\text{ACE})$$

$$\sigma_c^2 = \sigma_{\text{ACE}}^2 - \text{cov}\,(\ell n\,\text{ARE},\ \ell n\,\text{ACE})$$

$$\sigma_{TE}^2 = \text{cov}\,(\ell n\,\text{ARE},\ \ell n\,\text{ACE}) \tag{3.3}$$

$$b = [E(\ell n\,\text{ARE}) - E(\ell n\,\text{ACE})]/2$$

$$E(\ell n TE) = [E(\ell n\,\text{ARE}) + E(\ell n\,\text{ACE})]/2.$$

MaCurdy (1985) describes the details of the estimation procedure applied in this analysis both to calculate parameter estimates and to compute the standard errors associated with these estimates.

Tables 3.2–M and 3.2–W report estimated values for the variances of measurement error obtained for six cross-sections corresponding to the calendar years 1979–1984, along with a set of pooled estimates that combines the data for all years. The designation "M" in the table title signifies results for men, and "W" indicates estimates for women. Each cross-section sample composition includes individuals for which both ARE and ACE are nonmissing and nonzero. Rows 1 and 2 present estimates and standard errors for the parameters σ_r^2 and σ_c^2, and rows 3 and 4 show the fraction of total variance attributable to measurement error for the two earnings variables.

These empirical findings generally support two conclusions. First, the extent of measurement error is less of a problem for ACE than it is for ARE; σ_c^2 accounts for a smaller proportion of σ_{ACE}^2 than σ_r^2 contributes to σ_{ARE}^2. Second, the amount of measurement error contaminating ACE is tiny except in the year 1979, when it is still small. Such evidence lends some confidence to the view that computed weekly earnings data provides an accurate picture of individuals' earnings experiences over the period of a year.

Cameron and MaCurdy (1988) provide a more sophisticated discussion of these findings, along with richer statistical specifications to detect the magnitude and the properties of measurement error in the two annual earnings variables ARE and ACE. This more exhaustive empirical study exploits the panel feature of the YNLS to relax several of the restrictions of model (3.2) and to examine the autocorrelation characteristics of measurement error as well. In addition, this analysis considers a variety of sample composition issues. While this

TABLE 3.2-M
Measurement Error Variance Estimates For Log Annual Earnings[a]
(standard errors in parentheses)

Parameter	1979	1980	1981	1982	1983	1984	Pooled
σ_r^2	.138	.274	.206	.136	.187	.198	.189
	(.037)	(.109)	(.039)	(.030)	(.034)	(.025)	(.018)
σ_c^2	.129	.022	.006	.054	.053	.016	.038
	(.053)	(.023)	(.024)	(.031)	(.027)	(.026)	(.012)
$\sigma_r^2/\sigma_{ARE}^2$	.274	.413	.232	.159	.215	.249	.234
$\sigma_c^2/\sigma_{ACE}^2$	.260	.054	.008	.070	.072	.026	.059

[a] Estimates based on Sample L described in Appendix A.

TABLE 3.2-W
Measurement Error Variance Estimates For Log Annual Earnings[a]

Parameter	1979	1980	1981	1982	1983	1984	Pooled
σ_r^2	.204	.134	.114	.167	.249	.150	.171
	(.046)	(.041)	(.025)	(.028)	(.035)	(.033)	(.014)
σ_c^2	.025	.147	.058	.047	-.008	.056	.048
	(.039)	(.077)	(.026)	(.025)	(.021)	(.042)	(.016)
$\sigma_r^2/\sigma_{ARE}^2$	.243	.182	.115	.138	.213	.140	.162
$\sigma_c^2/\sigma_{ACE}^2$	.038	.196	.062	.043	-.008	.057	.052

[a]Estimates based on sample L described in Appendix A.

other analysis indicates a number of qualifications that need to be kept in mind in evaluating the validity of the two main conclusions noted above, the main thrust of these conclusions survives.

3.4 *Characteristics of Weekly and Hourly Earnings*

The availability of weekly histories on earnings and hours of work supplied by the YNLS provides the opportunity to examine the pattern of a variety of dimensions characterizing youths' labor market experiences within annual periods, both across demographic groups and over time. The current sub-section exploits this information to explore the variation in various wage measures less aggregated than total annual earnings, while the following discussion investigates aspects of employment experiences.

Beginning with the topic of weekly earnings, there are three measures of average weekly wages that one can associate with an individual during a calendar year using data from the YNLS. For each week during a year, one can infer the variables:

$$WE_\ell = \text{ weekly earnings from all jobs in week } \ell\text{; and}$$

$$WH_\ell = \text{ weekly hours from all jobs in week } \ell,$$

with $\ell = 1, \ldots, 52$ signifying the length of a calendar year.[3] Upon calculating the quantity

$$AWW = \text{ annual weeks worked,}$$

one can compute the following three variables for each individual:

$$ARE/AWW = \text{ weekly reported earnings;}$$

$$ACE/AWW = \text{ weekly computed earnings; and}$$

$$AVE(WE) = \sum_{\ell=1}^{52} WE_\ell/AWW.$$

The first two quantities merely represent familiar measures obtained by dividing annual earnings by weeks worked. The latter quantity denotes a simple average of an individual's weekly earnings over a year.

[3] In constructing the annual measure ACE, we use the actual calendar year which involves slightly more than 52 weeks. See Appendix A for further discussion.

Table 3.3–M for men and Table 3.3–W for women present summary statistics describing the variation in the three measures of average weekly earnings across persons of various age-education categories over the calendar years 1979–1984. These tables, and the remaining ones presented in this sub-section, have exactly the same structure as Tables 3.1. The top of each column lists the variable to which the numbers refer, and the three estimated values in each box represent the coefficient estimate θ_j of regression model (3.1) (the top number) along with the 25th and 75th percentiles associated with observations in the relevant demographic category (the lower two numbers). The six numbers reported at the bottom of each column are the estimated year effects γ_k associated with regression model (3.1).

Comparing summary statistics for the alternative measures of average weekly earnings listed in the first three columns of Tables 3.3 reveals general agreement among the results associated with these measures. For the older and more educated groups, the findings are quite similar. For the younger and less educated categories, there is tendency for the hourly reported earnings to indicate slightly lower weekly wages than the other two measures. In light of the results presented in Tables 3.1, this lower tendency no doubt partially reflects differences in the sample compositions used to compile the statistics in the various columns. These findings are consistent with the view that the younger and less educated individuals with intermittent jobs – whose earnings observations are not included in the statistics describing the measures ACE/AWW and $AVE(WE)$ – tend to have lower weekly earnings than their counterparts. The estimates for year effects reported in the bottom rows of the table indicate that weekly earnings declined over the period 1979–1984.

In addition to these various averages, Tables 3.3 also present results to capture the extent to which a person's own weekly wage varies within a calendar year. Define Max(WE) and Min(WE) as the maximum value and the minimum value, respectively, of WE_ℓ over weeks $\ell = 1, \ldots, 52$ for which both WE_ℓ and WH_ℓ have nonzero and nonmissing values. Form the quantities:

$$RR(WE) = \ell n\ (\mathrm{Max}(WE)/\mathrm{Min}(WE)) = \mathrm{Max}(\ell n WE) - \mathrm{Min}(\ell n WE);\ \text{and}$$

$$AR(WE) = \mathrm{Max}(WE) - \mathrm{Min}(WE).$$

The measure RR captures the notion of a "relative range" (or percentage difference) for the variable WE over the year, and AR represents an "absolute range" for WE. As in the case

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TABLE 3.3-M

Summary Statistics for Measures of Weekly Earnings *

(1984 $)

VARIABLE		ARE/AWW $			ACE/AWW $			AVE(WE) $			RR(WE)			AR(WE) $		
Educ	Age															
8+	18-19	110	210	264	160	229	280	154	229	274	0.00	0.37	0.49	0	75	104
	20-22	140	246	303	178	270	320	174	263	314	0.00	0.31	0.43	0	79	100
	23-24	146	274	331	182	292	342	181	298	348	0.02	0.29	0.40	3	87	89
	25-27	158	333	372	189	343	379	186	325	375	0.00	0.29	0.51	0	105	120
12	18-19	139	226	285	170	247	299	167	249	300	0.02	0.41	0.56	4	88	127
	20-22	178	290	361	204	307	373	197	298	364	0.03	0.31	0.42	8	84	108
	23-24	218	350	418	243	368	426	231	359	417	0.02	0.26	0.31	7	92	97
	25-27	239	384	461	258	397	448	251	392	442	0.02	0.21	0.29	5	84	102
13+	20-22	198	310	373	228	316	379	221	311	377	0.06	0.34	0.48	17	93	125
	23-24	226	360	436	243	380	461	233	364	442	0.06	0.30	0.39	15	103	117
	25-27	223	389	469	227	387	480	229	390	496	0.04	0.25	0.29	10	96	106
16+	23-24	261	392	484	288	419	503	269	403	497	0.07	0.32	0.43	20	100	135
	25-27	292	473	591	333	505	584	319	493	578	0.03	0.27	0.29	10	118	116
Year/Effects																
79	80	37		12	58		18	48		19	-0.00		-0.04	19		-2
81	82	2		-8	-1		-12	0		12	0.02		-0.02	4		-11
83	84	-21		-21	-22		-35	-28		-27	0.00		0.04	-10		-1

* For education-age groups, upper entry is the mean and lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

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TABLE 3.3-W

Summary Statistics for Measures of Weekly Earnings*

(1984 $)

VARIABLE		ARE/AWW $			ACE/AWW $			AVE(WE) $			RR(WE)			AR(WE) $		
Educ	Age		127			147			146			0.27			38	
8	18-19	72		171	101		184	104		185	0.00		0.35	0		50
			148			166			167			0.25			37	
	20-22	78		189	111		202	109		201	0.00		0.31	0		48
			169			183			178			0.27			47	
	23-24	82		207	107		217	96		217	0.00		0.34	0		52
			162			183			185			0.34			49	
	25-27	93		209	95		228	98		235	0.00		0.47	0		74
			163			179			173			0.35			53	
12	18-19	101		208	130		220	126		214	0.02		0.45	3		70
			188			200			195			0.27			47	
	20-22	116		240	146		244	141		241	0.00		0.32	1		59
			202			212			208			0.26			44	
	23-24	113		251	144		258	134		254	0.00		0.30	0		54
			217			224			219			0.22			39	
	25-27	115		276	140		274	129		272	0.00		0.33	0		53
			209			225			220			0.30			55	
13+	20-22	140		268	167		272	162		269	0.04		0.36	9		69
			236			246			245			0.25			54	
	23-24	161		301	174		297	166		293	0.02		0.27	5		62
			257			265			277			0.26			59	
	25-27	169		324	182		326	182		323	0.04		0.38	7		79
			287			301			295			0.32			79	
16+	23-24	209		350	227		367	219		349	0.05		0.43	11		107
			323			321			318			0.30			62	
	25-27	234		394	213		403	213		395	0.05		0.30	12		77
Year Effects																
79	80	13.3		5.5	17.2		10.6	18		12	-0.02		-0.02	1		0
81	82	2.6		-6.8	1.3		-8.7	1		-8	-0.00		-0.00	1		-3
83	84	-8.5		-6.0	-10.4		-10.0	-11		-11	0.02		0.04	-0		2

* For education-age groups, upper entry is the mean and lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

of the averages discussed above, one can calculate a value for RR and AR for each individual in each calendar year and use these data as dependent variables in regression model (3.1).

The fourth and the fifth columns of Tables 3.3–M and 3.3–W report the findings associated with these variables. According to these results, individuals experience large variation in weekly earnings within calendar years. Percentage changes (i.e. RR) average about 30 percent, with a quarter of individuals experiencing around 40 percent or more. Estimates for absolute ranges (i.e. AR) indicate average changes of about \$100 (in 1984 dollars) in weekly wages, with a quarter of individuals experiencing changes of about \$10 to \$20 above the averages.

One can construct a set of measures for hourly earnings that are completely analogous to those formulated above for weekly earnings. Given the quantities

$$AH = \sum_{\ell=1}^{52} WH_\ell = \text{ annual hours at all jobs}$$

and

$$AH_- = \text{ annual hours at all jobs for which wage data are nonmissing,}$$

the three measures of a person's average hourly wages earned over a year are:

$$ARE/AH = \text{ hourly reported earnings;}$$

$$ACE/AH_- = \text{ hourly computed earnings; and}$$

$$AVE(WE/WH) = \left[\sum_{\ell=1}^{52} WE_\ell/WH_\ell\right]/AWW = \text{ the average of hourly earnings for those weeks in which a person works,}$$

where in the calculation of this average, $WE_\ell/WH_\ell = 0$ when either $WE_\ell = 0$ or $WH_\ell = 0$. Also similar to the range variables introduced above, one can calculate:

$$RR(WE/WH) = \ell n\ (\text{Max}(WE/WH)) - \ell n(\text{Min}(WE/WH)); \text{ and}$$

$$AR(WE/WH) = \text{Max}(WE/WH) - \text{Min}(WE/WH).$$

Respectively, these variables capture the relative and the absolute ranges of an individual's hourly wages earned within the year.

Tables 3.4–M and 3.4–W present summary statistics for the five variables formed above to characterize the hourly earnings of youths. The first three columns report findings for

Table 3.4-M
Summary Statistics for Measures of Hourly Earnings*
(1984 $)

EDUC	AGE	ARE/AH (cents) mean	ARE/AH 25%	ARE/AH 75%	ACE/AH_ (cents) mean	ACE/AH_ 25%	ACE/AH_ 75%	AVE(WE/WH) (cents) mean	AVE(WE/WH) 25%	AVE(WE/WH) 75%	RR(WE/WH) mean	RR(WE/WH) 25%	RR(WE/WH) 75%	AR(WE/WH) (cents) mean	AR(WE/WH) 25%	AR(WE/WH) 75%
8+	18-19	520	289	626	552	403	618	558	403	615	0.29	0.00	0.38	154	0	194
	20-22	612	343	721	628	430	715	632	431	721	0.25	0.00	0.34	151	0	190
	23-24	654	342	790	695	433	799	699	434	806	0.27	0.02	0.35	178	10	194
	25-27	721	383	792	719	435	764	724	436	785	0.25	0.00	0.31	201	0	215
12	18-19	556	354	673	595	426	714	598	425	716	0.29	0.03	0.39	160	8	215
	20-22	692	427	859	700	473	853	702	474	82	0.24	0.03	0.33	163	15	208
	23-24	803	494	964	812	535	942	816	535	951	0.22	0.02	0.27	169	16	193
	25-27	877	555	1093	895	592	1043	904	591	1048	0.19	0.02	0.24	164	12	184
13+	20-22	728	440	863	721	511	840	720	510	829	0.28	0.07	0.37	188	43	229
	23-24	827	527	1002	838	557	1025	841	556	1026	0.27	0.05	0.36	223	27	257
	25-27	917	506	1078	928	553	1082	929	554	1084	0.22	0.02	0.25	207	19	208
16+	23-24	902	601	1134	902	601	1108	929	610	1118	0.29	0.06	0.31	228	40	285
	25-27	1098	682	1334	1135	729	1349	1122	729	1361	0.25	0.05	0.31	255	54	291

Year Effects		ARE/AH		ACE/AH_		AVE(WE/WH)		RR(WE/WH)		AR(WE/WH)	
79	80	93	28	101	51	106	49	0.02	-0.01	49	6
81	82	7	-21	7	-21	4	-21	0.01	-0.01	6	-23
83	84	-42	-65	-66	-72	-66	-72	-0.02	0.2	-26	-12

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

Table 3.4-W
Summary Statistics for Measures of Hourly Earnings*
(1984 $)

VARIABLE		ARE/AH (cents)			ACE/AH_ (cents)			AVE(WE/WH) (cents)			RR(WE/WH)			AR(WE/WH) (cents)		
EDUC	AGE		387			421			423			0.18			69	
8+	18-19	232		477	356		501	357		501	0.00		0.22	0		95
			428			466			470			0.16			77	
	20-22	245		480	358		533	357		534	0.00		0.21	0		96
			465			485			487			0.19			91	
	23-24	267		538	356		548	352		549	0.00		0.23	0		106
			497			533			532			0.17			88	
	25-27	258		541	363		584	364		585	0.00		0.31	0		149
			450			471			473			0.24			109	
12	18-19	309		544	384		551	385		549	0.01		0.28	5		139
			511			526			530			0.21			105	
	20-22	343		613	397		613	400		617	0.00		0.26	0		130
			566			566			568			0.20			104	
	23-24	356		673	398		662	400		660	0.00		0.24	0		123
			592			595			598			0.15			88	
	25-27	346		702	412		691	412		688	0.00		0.22	0		115
			544			575			576			0.22			116	
13+	20-22	397		668	438		655	439		659	0.03		0.28	15		148
			639			640			641			0.21			118	
	23-24	419		778	457		770	456		770	0.02		0.26	12		150
			693			715			719			0.19			120	
	25-27	420		832	480		878	478		875	0.05		0.26	25		150
			747			751			755			0.28			192	
16+	23-24	521		887	551		911	550		915	0.04		0.36	24		242
			868			826			829			0.26			147	
	25-27	565		1015	522		967	517		974	0.03		0.24	23		180
Year Effects																
79	80	40.3		15.8	42.2		29.6	44		30	-0.01		-0.01	5		-1
81	82	-5.0		-2.0	.6		-16.1	1		-16	-0.01		-0.01	4		-5
83	84	-24.2		-32.9	-25.1		-31.2	-26		-32	0.00		0.03	-4		2

* For education-age groups, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

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averages, and the fourth and the fifth columns list results for the two range measures. These statistics outline essentially the same picture as that portrayed by the result for weekly earnings presented in Tables 3.3. This is true for the pattern of both the average and the ranges of hourly earnings across age-education groups, as well as the profiles over time.

3.5 *Characteristics of Employment Activities*

There are a wide variety of variables that one can infer from the weekly work histories of the YNLS to describe the employment activities of youths during calendar years. The above discussion of earnings already introduced several of these variables, and this analysis formulates a few additional quantities to provide a richer characterization of work experience.

Tables 3.5–M and 3.5–W report summary statistics for quantities capturing the fraction of a year that individuals work and the number of jobs that they hold during the year. The first column presents results for the quantity

$DAEMP =$ dummy variable for whether an individual is employed at any time during the year ($DAEMP = 1$ signifies employment).

This variable, of course, characterizes annual employment rates. The second column of Tables 3.5 reports statistics for the number of weeks worked per year, (AWW), and the third column lists estimates for the variable

$$AEMPS = \text{ number of employers over the year.}$$

$AEMPS$ does not capture the extent to which individuals hold multiple jobs at the same time because a person can work for different employers at distinct times during the year. To provide measures of the extent of simultaneous job holding, the fourth, fifth and sixth columns of these tables present statistics for the variables:

$ADMJ =$ dummy variables signifying whether an individual holds multiple jobs in any week during the year ($ADMJ = 1$ indicates simultaneous jobs);

$AWMJ =$ number of weeks associated with multiple jobs; and

$AWMJ/AWW =$ fraction of total weeks worked in which multiple jobs were held.

TABLE 3.5-M

Summary Statistics for Weeks Worked and Jobs Per Year[a]

EDUC.	AGE	DAEMP	AWW mean	AWW 25%	AWW 75%	AEMPS mean	AEMPS 25%	AEMPS 75%	ADMJ	AWMJ mean	AWMJ 25%	AWMJ 75%	AWJ/AWW mean	AWJ/AWW 25%	AWJ/AWW 75%
8+	18-19	89.0	36	22	51	1.9	1.0	2.0	8.9	13	4	19	34	12	58
	20-22	91.1	39	29	52	1.6	1.0	2.0	8.1	13	4	19	30	10	44
	23-24	91.9	42	34	52	1.6	1.0	2.0	9.3	17	5	33	37	11	75
	25-27	91.3	40	32	52	1.6	1.0	2.0	5.9	29	10	42	58	40	79
12	18-19	96.4	43	38	52	1.7	1.0	2.0	14.9	22	7	40	43	13	77
	20-22	97.7	45	43	52	1.6	1.0	2.0	13.3	22	7	40	43	14	77
	23-24	97.7	46	45	52	1.5	1.0	2.0	13.8	24	8	41	47	19	79
	25-27	97.0	47	47	52	1.4	1.0	2.0	11.7	27	13	45	55	24	88
13+	20-22	99.0	46	46	52	1.7	1.0	2.0	15.4	19	6	33	37	12	61
	23-24	99.9	48	49	52	1.7	1.0	2.0	15.5	22	5	49	44	13	92
	25-27	99.9	47	46	52	1.5	1.0	2.0	14.0	20	6	38	42	18	73
16+	23-24	97.8	49	50	52	1.6	1.0	2.0	16.6	24	9	44	47	17	84
	25-27	98.7	50	52	52	1.4	1.0	2.0	17.5	23	9	42	44	18	80

Year	Effects	DAEMP	DAEMP	AWW	AWW	AEMPS	AEMPS	ADMJ	ADMJ	AWMJ	AWMJ	AWJ/AWW	AWJ/AWW
79	80	3.1	0.4	2	0	0.1	-0.1	-0.2	-3.1	-4	0	-8	-0
81	82	0.1	-1.5	-0	-1	-0.0	-0.1	-0.1	-0.0	-1	2	-2	3
83	84	-2.1	0.1	-1	0	-0.0	0.1	1.4	2.9	2	1	5	2

a For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.5-W
Summary Statistics for Weeks Worked and Jobs Per Year*

VARIABLE EDUC.	AGE	DAEMP	AWW			AEMPS			ADMJ	AWMJ			AWJ/AWW		
			mean	25%	75%	mean	25%	75%		mean	25%	75%	mean	25%	75%
8+	18-19	64.6	28	13	45	1.7	1.0	2.0	7.6	12	4	15	30	12	43
	20-22	62.4	31	15	50	1.5	1.0	2.0	7.5	13	4	19	29	8	44
	23-24	54.9	34	18	52	1.5	1.0	2.0	10.2	16	6	23	39	13	63
	25-27	52.4	31	15	50	1.3	1.0	1.0	3.9	14	3	30	29	5	59
12	18-19	90.3	41	33	52	1.7	1.0	2.0	13.4	15	5	21	31	11	46
	20-22	84.2	41	33	52	1.5	1.0	2.0	11.5	19	6	28	40	13	65
	23-24	80.5	41	34	52	1.4	1.0	2.0	10.9	19	7	30	41	19	65
	25-27	77.2	42	35	52	1.3	1.0	2.0	8.6	24	11	42	50	24	83
13+	20-22	91.9	45	42	52	1.6	1.0	2.0	18.2	19	7	27	41	13	61
	23-24	91.5	44	42	52	1.4	1.0	2.0	12.9	25	9	46	48	17	94
	25-27	88.1	44	42	52	1.4	1.0	2.0	13.4	19	8	29	40	18	59
16+	23-24	98.0	47	45	52	1.6	1.0	2.0	17.5	17	6	26	33	12	50
	25-27	92.6	46	43	52	1.4	1.0	2.0	19.6	23	9	42	45	19	78

Year	Effects	DAEMP	DAEMP	AWW	AWW	AEMPS	AEMPS	ADMJ	ADMJ	AWMJ	AWMJ	AWJ/AWW	AWJ/AWW
79	80	0.2	0.0	0	0	0.0	0.1	-1.8	-1.0	-2	-0	-5	-1
81	82	0.6	-1.1	-0	-1	-0.0	-0.1	-0.1	-0.0	-0	1	-1	3
83	84	-0.9	1.2	-0	1	0.0	0.0	1.9	1.0	2	-0	5	-1

* For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

The results for the variable $ADMJ$ reported in Tables 3.5 are computed using all available data and individuals, whereas the results for the variables $AWMJ$ and AWJ/AWW refer to samples incorporating only those persons for which $ADMJ = 1$.

The findings in Tables 3.5 generally convey a picture of extensive annual employment participation and only a modest amount of simultaneous job holding. As one would predict, labor-market involvement is greater for men than for women; and it generally rises with age and education in the case of men, but follows a nonmonotonic relationship in the case of women.

Tables 3.6–M and 3.6–W describe the variation in annual and weekly hours of work across the various age-education categories and over time. The previous discussion defines all the variables appearing in these tables. Comparing the findings in the first and second columns reveals that wage data are missing for only 6% of annual hours (i.e. the average of $AH\_$ is roughly 0.94 times that of AH). However, as noted in Section A.5 of Appendix A, these missing wages affect over a quarter of the sample in any one year. In all of the subsequent work described in this report, missing wages are imputed, where possible, using the procedures outlined in Appendix A.

A more comprehensive examination of the full complement of results in these tables reveals a fairly wide dispersion in annual hours across the population, but a relatively narrow dispersion in average hours per week. The variables $AVE(WH)$, $RR(WH)$ and $AR(WH)$ are calculated only over those weeks in which an individual works. The measures of relative and absolute ranges suggest a large amount of person-specific variation in the number of hours that he or she works per week during times of employment in a year.

TABLE 3.6-M
Summary Statistics for Annual and Weekly Hours of Work*

EDUC.	AGE	AH			AH_			AVE(WH)			AR(WH)			RR(WH)		
8+	18-19		1515			1379			42			0.35			13	
		829		2088	638		2011	38		46	0.00		0.48	0		20
	20-21		1707			1603			42			0.24			10	
		1086		2124	955		2088	40		47	0.00		0.32	0		13
	23-24		1843			1746			43			0.24			9	
		1304		2294	1094		2180	40		48	0.00		0.32	0		12
	25-27		1843			1727			46			0.27			11	
		1174		2404	1025		2234	40		52	0.00		0.42	0		20
12	18-19		1812			1702			41			0.33			12	
		1400		2167	1270		2096	39		45	0.00		0.43	0		13
	20-22		1947			1849			43			0.26			10	
		1607		2282	1516		2188	40		46	0.00		0.32	0		13
	23-24		2078			1963			44			0.20			9	
		1771		2413	1626		2329	40		49	0.00		0.22	0		10
	25-27		2090			1989			44			0.15			7	
		1899		2374	1793		2312	40		48	0.00		0.21	0		10
13+	20-22		2033			1920			44			0.27			11	
		1723		2365	1523		2329	40		48	0.00		0.41	0		16
	23-24		2204			2028			45			0.25			11	
		1943		2476	1778		2312	40		49	0.00		0.32	0		15
	25-27		2083			1981			44			0.22			9	
		1843		2407	1679		2309	40		48	0.00		0.33	0		[illegible]
16+	23-24		2204			2117			45			0.23			9	
		1980		2545	1871		2482	40		50	0.00		0.26	0		10
Year	Effects															
79	80	88		6	61		18	1		-0	-0.02		-0.04	-0		-2
81	82	-29		-51	-13		-42	-0		-0	-0.02		-0.04	-0		-2
83	84	-62		47	-55		31	-0		1	0.03		0.05	1		2

* For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

TABLE 3.6-W
Summary Statistics for Annual and Weekly Hours of Work*

VARIABLE		AH			AH_			AVE(WH)			RR(WH)			AR(WH)		
EDUC.	AGE															
8+	18-19		1015			913			35			0.31			10	
		382		1608	277		1486	29		40	0.00		0.47	0		16
	20-21		1152			1066			35			0.28			8	
		472		1834	363		1768	30		40	0.00		0.36	0		13
	23-24		1269			1187			36			0.26			8	
		560		2080	380		2012	28		40	0.00		0.35	0		11
	25-27		1065			987			33			0.26			7	
		400		1755	288		1594	22		40	0.00		0.26	0		10
12	18-19		1500			1423			36			0.33			10	
		945		2088	804		2073	33		40	0.00		0.47	0		15
	20-22		1564			1495			37			0.24			8	
		1044		2088	922		2088	35		40	0.00		0.29	0		10
	23-24		1560			1487			36			0.25			7	
		1043		2088	919		2088	32		40	0.00		0.29	0		10
	25-27		1558			1465			36			0.24			6	
		1000		2088	840		2080	33		40	0.00		0.28	0		10
13+	20-22		1759			1646			39			0.28			9	
		1432		2096	1269		2088	36		41	0.00		0.30	0		11
	23-24		1743			1660			38			0.22			7	
		1422		2088	1288		2088	35		40	0.00		0.22	0		9
	25-27		1717			1619			38			0.25			7	
		1253		2088	1224		2083	35		41	0.00		0.34	0		14
16+	23-24		1894			1811			40			0.30			10	
		1577		2182	1480		2088	38		44	0.00		0.41	0		15
	25-27		1840			1745			39			0.19			6	
		1436		2302	1203		2088	37		45	0.00		0.27	0		10
Year Effects																
79	80	13.4		13.6	9.1		7.8	0		-0	-0.04		0.01	-1		-0
81	82	1.1		-46.9	10.1		-39.1	0		-1	-0.00		-0.01	-0		-0
83	84	18.3		37.1	-29.5		41.6	-0		0	0.03		0.01	1		1

* For education-age group, upper entry is the mean and the lower two entries are the 25% and 75% quartiles. For year effects, entries are annual deviations of means listed by year in sequence listed.

4. UI Eligibility and Use Among Young Workers

A major source of controversy in the literature about the influence of UI policies on the amount of unemployment experienced by youths in the U.S. turns on the issue of the extent to which youths participate in the UI system. Whereas many empirical studies suggest that both the level of weekly UI benefits and the duration of these benefits exert a significant effect on the extent of unemployment,[4] other studies argue that UI programs play only a minor role in youth unemployment because most young people are ineligible for compensation from these programs.[5]

This section presents an array of measures designed to describe UI coverage and UI utilization among young workers during the years 1979–84. The analysis relies on the work history data described in the previous section to impute UI eligibility and benefits and combines the information with data provided by the YNLS on UI collection over the year to calculate the measures developed below. The discussion constructs measures considering several period lengths as the relevant time frame and viewing both nonemployment and unemployment as the pertinent base for calculating eligibility and usage of UI.

4.1 *Measures of Eligibility*

Considering a period covering one year, there are several ways of measuring the eligibility of an individual for UI compensation. In particular, one can designate a person as eligible for UI if he or she is not working sometime during the year and this individual is qualified to collect UI benefits. Such a classification scheme suggests the measure

$$E/N = \frac{\#\ \text{eligible}}{\#\ \text{nonemployed}} \tag{4.1}$$

where the quantity "# eligible" designates the number of individuals who are deemed qualified for UI compensation at sometime during the year, and the quantity "# nonemployed" represents the number of individuals who are not employed during some part of the year. (Of course, # eligible is necessarily a subset of # nonemployed; so E/N ranges between zero and one.)

[4] Examples of such studies include Feldstein (1978), Hammermesh (1977), Topel and Welch (1980), Ehrenberg and Oaxaca (1976), Newton and Rosen (1979), Moffitt and Nicholson (1982), and Clark and Summers (1982a).

[5] See, for example, Feldstein and Ellwood (1982) and Clark and Summers (1979).

Suppose that one wishes to calibrate this measure to weight individuals according to the fraction of nonemployment time during the year that they were qualified for UI compensation. A second measure incorporating such a calibration is

$$(4.2) \qquad \begin{aligned} we/wn &= \frac{\text{\# weeks eligible}}{\text{\# weeks nonemployed}} \\ WE/WN &= Ave\,\{we/wn\} \end{aligned}$$

where the quantity "# weeks eligible" gives the number of weeks during a year in which a person is eligible for UI benefits, the quantity "# weeks nonemployed" designates the number of weeks that this person spent not working during the year, and the notation $Ave\,\{\cdot\}$ denotes the average of the variable in brackets computed over individuals making up a sample.

Instead of considering nonemployment as the relevant frame of reference as is presumed by the above measures, suppose that one views unemployment status as the proper reference perspective for assessing the extent of eligibility. Modifying the measure E/N to reflect this adjustment yields a third measure given by

$$(4.3) \qquad E/U = \frac{\text{\# eligible}}{\text{\# unemployed}}$$

where the quantity "# unemployed" represents the number of individuals who are classified as unemployed at sometime during the year. (Note that "# eligible" need not be a subset of "# unemployed", so E/U can in principle go above one in value.) Similarly, an analogous modification of WE/WN yields a fourth measure given by

$$(4.4) \qquad \begin{aligned} we/wu &= \frac{\text{\# weeks eligible}}{\text{\# weeks unemployed}} \\ WE/WU &= Ave\,\{we/wu\} \end{aligned}$$

where the quantity "# weeks unemployed" denotes the number of weeks that an individual reports as being unemployed during the year.

The variables WE/WN and WE/WU correspond to average point-in-time measures of eligibility, while the variables E/N and E/U reflect notions of eligibility over a period lasting a year. Assuming a random sample of individuals and a stationary environment, (4.2) and (4.4) give proxies for the kind of eligibility measures derived from CPS-type information concerning weekly status: WE/WN corresponds to the ratio of the number of persons eligible

for UI in a survey week over the number not working; and WE/WU measures the ratio of the number of eligible persons in a survey week over the number reported as unemployed. The variables E/N and E/U have analogous interpretations if one adjusts the period of observation from a survey week to a survey year.

4.2 *Measures of Utilization*

Considering a period covering one year, there are several quantities describing the extent to which individuals eligible for UI compensation draw on their available benefits. A direct translation of the concept introduced above yields the following two measures:

$$R/E = \frac{\#\text{ recipients}}{\#\text{ eligible}} \tag{4.5}$$

and

$$\begin{aligned} wr/we &= \frac{\#\text{ weeks receipt}}{\#\text{ weeks eligible}} \\ WR/WE &= Ave\,\{wr/we\} \end{aligned} \tag{4.6}$$

where the quantity "# recipients" designates the number of individuals who collect UI benefits during the year, and the quantity "# weeks receipt" represents the number of weeks during the year in which UI recipients draw benefits. (Both R/E and WR/WE must lie between zero and one because a person cannot collect benefits unless he or she is eligible for compensation). Whereas the variable R/E corresponds to an annual utilization measure of UI programs, the variable WR/WE reflects a point-in-time measure of use.

The most popular statistic cited to describe the degree of UI utilization is the ratio of insured unemployment over total unemployment, which implicitly takes all those who are unemployed as the relevant frame of reference for calculating usage. A measure based on this statistic is

$$\begin{aligned} wr/wu &= \frac{\#\text{ weeks receipt}}{\#\text{ weeks unemployed}} \\ WR/WU &= Ave\,\{wr/wu\}. \end{aligned} \tag{4.7}$$

This quantity represents an annualized average of a point-in-time measure of usage.

A measure comparable to WR/WU takes time spent nonemployed rather than time spent unemployed as the appropriate reference for guaging the extent of UI utilization. This

quantity is

$$
\begin{aligned}
&wr/wr = \frac{\#\text{ weeks receipt}}{\#\text{ weeks nonemployed}} \\
(4.8)\qquad & \\
&WR/WN = Ave\{wr/wu\},
\end{aligned}
$$

which provides another measure of an annualized average of point-in-time usage.

A fifth concept of utilization summarizes the fraction of the dollar amounts of UI entitlements that are actually collected during the year by eligible individuals. A measure capturing this concept is given by

$$
\begin{aligned}
&ar/ae = \frac{\$\text{ amount received}}{\$\text{ amount eligible}} \\
(4.9)\qquad & \\
&AR/AE = Ave\,\{ar/ae\}
\end{aligned}
$$

where the quantity "$ amount received" denotes the number of dollars an individual collects in UI benefits during the year, and the quantity "$ amount eligible" designates the maximum dollar amount of UI compensation that the individual could have collected had he or she drawn benefits during all weeks of eligibility in the year.

4.3 *A Data Set Integrating UI Eligibility and Utilization*

To calculate the various measures discussed above, the following analysis uses a sample created by more stringent selection criteria than are invoked to carry out the empirical study of Section 3. The sample considered here consists of 3028 individuals drawn from the nationally-representative component of 6,111 youths in the YNLS who met the following five conditions: (1) interviewed in each of the first 7 years; (2) worked at least once since January 1979; (3) have valid beginning and ending dates for time periods spent employed, between jobs and in the military; (4) left school and did not return prior to the 1985 interview date; and (5) have a reasonably accurate and complete time series of weekly earnings beginning with January 1978 or the last date of school attendance. As noted previously, the YNLS does not provide wage data for secondary jobs of short duration or which involve only part-time hours of work. For jobs falling into this category determined to be in covered employment, the analysis assigns wages using a procedure described in Appendix A to avoid having to delete observations from the sample. The resulting data set includes 1409 men and 1619

women who experience 4031 and 4250 episodes of nonemployment respectively over the period 1979–85. Section 6.1 presents summary statistics describing this data set in detail.

For each calendar year, the YNLS provides not only comprehensive information on work histories as described in Section 3, but also reliable data on the total number of weeks that a youth receives UI payments during the year along with the average weekly benefit amount over this period. Combining an individual's weekly earnings history in covered employment with data on his or her State of residency and the UI benefit rules of that State in the relevant year, one can infer this person's UI eligibility and available benefits during times of nonemployment and unemployment. These constructed data provide the sample used below to calculate measures of UI eligibility. Integrating these data and the information on time and amounts of UI collection during the calendar year create the sample exploited below to carry out the analysis on UI utilization.

Appendix B outlines our procedure for inferring each individual's UI entitlements during periods of nonemployment. As discussed in this appendix, our imputation of available UI benefits yields remarkable accurate predictions of the average weekly benefit amounts that are self-reported by UI recipients in the YNLS. The differences in our imputed values and the values reported in the YNLS averages about $2, with lower and upper quartiles of −$11 and $20. Our assessment of UI eligibility and of total benefits available from UI compensation also appear to match well with data provided in the YNLS on the total number of weeks a youth receives UI payments over the year and the months in which benefits were collected.

For determining UI eligibility, the YNLS offers two options for defining job separations due to quits as a disqualification for benefits. Major reasons for disqualification from UI benefit receipt are voluntary separations without good cause, discharge for mis-conduct, refusal of suitable work and unemployment resulting from direct involvement in an organized labor stoppage. Unfortunately, the current literature has interpreted the provision for voluntarily leaving work without good cause to mean that all "quitters" are ineligible to receive UI benefits. While such provisions are often ambiguously phrased, the majority of states do not disqualify individuals who quit for reasons related to the employment relationship. A large number of states allow an individual to collect benefits if he or she quit to accept

"better" work or join the armed forces. Thus, in practice this provision usually disqualifies only those individuals who quit for personal reasons.[6] To examine the sensitivity of results to alternative interpretations of voluntary separation provisions in deciding an individual's eligibility for UI, the following analysis considers two definitions of eligibility: a narrow concept that presumes all persons who quit their previous job are ineligible for compensation, and a broader definition that disqualifies individuals only if they quit for personal reasons.

4.4 *Patterns of UI Eligibility*

There are two dimensions of interest for calculating the various measures of UI eligibility and of UI use: the first involves a comparison across different education and age groups; and the second focuses on the time path of these measures. This analysis considers both of these dimensions. It does so by decomposing each measure into age-education and time effects using regression framework (3.1) introduced in Section 3.1, with the dependent variable y_{it} denoting an observation associated with an eligibility or utilization measure for the i^{th} individual in year t.[7] As previously, the coefficient γ_k represents the average of y associated with age-education group k over the period 1 to T, and the θ_j's represent the common deviation experienced by all groups in year j ($j = 1, \ldots, T$). The age-education categories considered below are the same as those analyzed in Section 3, as are the calendar years.

Tables 4.1 and 4.2 present values for the four measures of UI eligibility, with the averages calculated using estimates of the regression coefficients of equation (3.1). The tables designated by "M" provide results for men, while those marked by "W" report findings for women. Tables 4.1–M and 4.1–W present estimates of the coefficients γ_k, which characterize averages for the various age-education groups. Tables 4.2–M and 4.2–W list estimates of the coefficients $\theta_j + \gamma_k$ for $j = 1979, \ldots, 1984$ with k designating 25 year-old high school graduates, which describes changes over time using the 25–27 age category of high school

[6] A casual survey of the data on benefit determination cases suggests that only 15–20 percent of new insured unemployment spells come to a determination over separation from work issues and only 30–40 percent of the cases that come to determination are denied because of voluntary separation from work.

[7] For the measures E/N, E/U and R/E, y_{it} is an indicator variable that takes the value of one when individual i is a member of the groups making up the numerator and the denominator and takes the value of zero if this individual is a member of only the denominator group. In the case of the other measures, such as WE/WN, $y_{it} = we/wn$ where the variable we/wn is the observation for individual i in year t.

TABLE 4.1-M

Measures of Unemployment Insurance Eligibility by Age-Education Categories

Catagory		Broad Definition of Eligiblity Measure				Narrow Definition of Eligibility Measure			
Education	Age	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
8-11	18-19	0.413	0.325	0.446	0.642	0.256	0.175	0.307	0.335
	20-22	0.532	0.421	0.594	0.743	0.394	0.284	0.447	0.449
	23-24	0.656	0.526	0.732	0.753	0.547	0.405	0.625	0.577
	25-27	0.533	0.427	0.602	0.651	0.397	0.279	0.489	0.433
12	18-19	0.486	0.419	0.601	0.910	0.287	0.219	0.399	0.416
	20-22	0.596	0.495	0.694	0.787	0.475	0.369	0.600	0.608
	23-24	0.659	0.553	0.785	0.819	0.541	0.436	0.663	0.631
	25-27	0.689	0.583	0.785	0.832	0.547	0.440	0.671	0.632
13-15	20-22	0.480	0.413	0.581	1.213	0.301	0.243	0.411	0.622
	23-24	0.520	0.468	0.663	1.229	0.313	0.256	0.433	0.635
	25-27	0.607	0.559	0.748	0.880	0.416	0.338	0.585	0.532
16	23-24	0.492	0.472	0.750	1.242	0.325	0.281	0.490	0.559
	25-27	0.685	0.609	0.870	0.881	0.343	0.287	0.350	0.299

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TABLE 4.1-W

Measures of Unemployment Insurance Eligibility by Age-Education Categories

Catagory		Broad Definition of Eligiblity Measure				Narrow Definition of Eligibility Measure			
Education	Age	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
8-11	18-19	0.243	0.179	0.303	0.835	0.118	0.076	0.157	0.321
	20-22	0.311	0.205	0.449	0.823	0.158	0.105	0.253	0.376
	23-24	0.283	0.223	0.379	0.777	0.147	0.113	0.236	0.380
	25-27	0.291	0.199	0.323	0.633	0.130	0.089	0.207	0.278
12	18-19	0.397	0.329	0.457	0.904	0.195	0.149	0.263	0.410
	20-22	0.360	0.275	0.484	1.184	0.193	0.137	0.285	0.439
	23-24	0.311	0.231	0.481	0.887	0.154	0.114	0.289	0.431
	25-27	0.344	0.243	0.560	1.102	0.197	0.132	0.387	0.694
13-15	20-22	0.319	0.274	0.421	1.132	0.120	0.103	0.196	0.259
	23-24	0.364	0.299	0.492	0.894	0.126	0.103	0.206	0.253
	25-27	0.292	0.218	0.465	0.763	0.112	0.082	0.215	0.318
16	23-24	0.435	0.340	0.514	0.724	0.218	0.165	0.213	0.365
	25-27	0.459	0.407	0.655	2.655	0.361	0.321	0.511	2.236

TABLE 4.2-M

Measures of Unemployment Insurance Eligibility by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Broad Definition of Eliigiblity				Narrow Definition of Eligibility			
	Measure				Measure			
	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
1979	0.803	0.722	0.919	0.956	0.603	0.500	0.776	0.696
1980	0.829	0.724	0.947	1.082	0.645	0.518	0.790	0.744
1981	0.807	0.682	0.904	1.096	0.591	0.477	0.702	0.695
1982	0.751	0.637	0.835	0.866	0.597	0.478	0.709	0.659
1983	0.569	0.430	0.652	0.599	0.487	0.376	0.590	0.572
1984	0.375	0.302	0.453	0.394	0.359	0.292	0.459	0.425
Average	0.689	0.583	0.785	0.832	0.547	0.440	0.671	0.632

TABLE 4.2-W

Measures of Unemployment Insurance Eligibility by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

	Broad Definition of Eligiblity				Narrow Definition of Eligibility			
	Measure				Measure			
Year	E/N	WE/WN	E/U	WE/WU	E/N	WE/WN	E/U	WE/WU
1979	0.361	0.291	0.558	1.657	0.151	0.110	0.320	0.952
1980	0.401	0.287	0.674	1.263	0.212	0.142	0.427	0.681
1981	0.451	0.318	0.698	1.247	0.221	0.148	0.418	0.715
1982	0.430	0.316	0.666	1.283	0.253	0.175	0.459	0.712
1983	0.260	0.150	0.437	0.736	0.193	0.121	0.375	0.587
1984	0.160	0.097	0.326	0.425	0.152	0.094	0.324	0.517
Average	0.344	0.243	0.560	1.102	0.197	0.132	0.387	0.694

graduates as a reference group. Each table reports two sets of results to examine the implications of adopting the two different definitions of eligibility described above. The first set of four columns list estimates assuming the broader definition, which interprets all nonemployed individuals who did not quit their jobs for personal reasons and who meet earnings qualifications as eligible for UI benefits. The second set of four columns presents results presuming applicability of the narrower definition of eligibility, which assumes that all quitters (for personal reasons or not) are ineligible.

According to these findings, the definition of eligibility matters with respect to one's assessment of the extent to which youths are eligible for UI benefits. The broader definition, which does not exclude all quitters, typically implies 50 to 100 percent greater eligibility over the narrow definition. There is no systematic relationship between annual and comparable point-in-time measures of eligibility.

Certain patterns emerge regardless of the definition or measure used to quantify eligibility. In the case of men, eligibility increases with both age and education. The same is true for women with respect to education, but not with regard to age. As expected, eligibility is more extensive for men than for women. For men, the results for time effects indicate that eligibility generally declined over the period 1979–1984, dramatically so for the broad definition of eligibility. The time trends are either less prominent or nonexistent for women.

4.5 *Patterns of UI Use*

Tables 4.3 and 4.4 report analogous estimates for the five measures of UI utilization. Tables 4.3–M and 4.3–W present values associated with age-education categories. Tables 4.4–M and 4.4–W list estimates for the time effects, with 25 year-old high school graduates serving as the reference group. Once again each table provides two sets of results according to the definitions used to determine eligibility. The measures considered in the first two columns of each table are not dependent on the definition of eligibility.

The first column of each table presents findings for that measure of utilization corresponding to the fraction of insured unemployment. Inspection of these results reveals that this rate rises with age in the case of men, but does not necessarily increase as men acquire more education. This same pattern holds in the case of women except for the lowest educa-

TABLE 4.3-M

Measures of Unemployment Insurance Utilization by Age-Education Categories

Catagory		Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
				Measure			Measure		
Education	Age	WR/WU	WR/WN	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
	18-19	0.076	0.050	0.181	0.137	0.129	0.276	0.216	0.204
8-11	20-22	0.202	0.119	0.246	0.193	0.188	0.294	0.239	0.233
	23-24	0.353	0.255	0.430	0.348	0.339	0.481	0.397	0.389
	25-27	0.311	0.202	0.553	0.452	0.447	0.579	0.483	0.478
	18-19	0.281	0.132	0.306	0.228	0.220	0.467	0.374	0.361
12	20-22	0.359	0.230	0.477	0.388	0.363	0.541	0.448	0.423
	23-24	0.456	0.322	0.594	0.482	0.470	0.652	0.547	0.534
	25-27	0.874	0.379	0.654	0.561	0.536	0.726	0.635	0.607
	20-22	0.146	0.090	0.198	0.165	0.144	0.294	0.250	0.218
13-15	23-24	0.249	0.165	0.319	0.280	0.262	0.454	0.431	0.402
	25-27	0.288	0.195	0.323	0.267	0.241	0.459	0.408	0.374
16	23-24	0.169	0.090	0.182	0.187	0.190	0.262	0.271	0.274
	25-27	0.694	0.247	0.346	0.359	0.352	0.408	0.428	0.433

graduates as a reference group. Each table reports two sets of results to examine the implications of adopting the two different definitions of eligibility described above. The first set of four columns list estimates assuming the broader definition, which interprets all nonemployed individuals who did not quit their jobs for personal reasons and who meet earnings qualifications as eligible for UI benefits. The second set of four columns presents results presuming applicability of the narrower definition of eligibility, which assumes that all quitters (for personal reasons or not) are ineligible.

According to these findings, the definition of eligibility matters with respect to one's assessment of the extent to which youths are eligible for UI benefits. The broader definition, which does not exclude all quitters, typically implies 50 to 100 percent greater eligibility over the narrow definition. There is no systematic relationship between annual and comparable point-in-time measures of eligibility.

Certain patterns emerge regardless of the definition or measure used to quantify eligibility. In the case of men, eligibility increases with both age and education. The same is true for women with respect to education, but not with regard to age. As expected, eligibility is more extensive for men than for women. For men, the results for time effects indicate that eligibility generally declined over the period 1979–1984, dramatically so for the broad definition of eligibility. The time trends are either less prominent or nonexistent for women.

4.5 *Patterns of UI Use*

Tables 4.3 and 4.4 report analogous estimates for the five measures of UI utilization. Tables 4.3–M and 4.3–W present values associated with age-education categories. Tables 4.4–M and 4.4–W list estimates for the time effects, with 25 year-old high school graduates serving as the reference group. Once again each table provides two sets of results according to the definitions used to determine eligibility. The measures considered in the first two columns of each table are not dependent on the definition of eligibility.

The first column of each table presents findings for that measure of utilization corresponding to the fraction of insured unemployment. Inspection of these results reveals that this rate rises with age in the case of men, but does not necessarily increase as men acquire more education. This same pattern holds in the case of women except for the lowest educa-

TABLE 4.3-M

Measures of Unemployment Insurance Utilization by Age-Education Categories

Catagory		Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
				Measure			Measure		
Education	Age	WR/WU	WR/WN	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
8-11	18-19	0.076	0.050	0.181	0.137	0.129	0.276	0.216	0.204
	20-22	0.202	0.119	0.246	0.193	0.188	0.294	0.239	0.233
	23-24	0.353	0.255	0.430	0.348	0.339	0.481	0.397	0.389
	25-27	0.311	0.202	0.553	0.452	0.447	0.579	0.483	0.478
12	18-19	0.281	0.132	0.306	0.228	0.220	0.467	0.374	0.361
	20-22	0.359	0.230	0.477	0.388	0.363	0.541	0.448	0.423
	23-24	0.456	0.322	0.594	0.482	0.470	0.652	0.547	0.534
	25-27	0.874	0.379	0.654	0.561	0.536	0.726	0.635	0.607
13-15	20-22	0.146	0.090	0.198	0.165	0.144	0.294	0.250	0.218
	23-24	0.249	0.165	0.319	0.280	0.262	0.454	0.431	0.402
	25-27	0.288	0.195	0.323	0.267	0.241	0.459	0.408	0.374
16	23-24	0.169	0.090	0.182	0.187	0.190	0.262	0.271	0.274
	25-27	0.694	0.247	0.346	0.359	0.352	0.408	0.428	0.433

TABLE 4.3-W

Measures of Unemployment Insurance Utilization by Age-Education Categories

Catagory		Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
				Measure			Measure		
Education	Age	WR/WU	WR/WN	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
8-11	18-19	0.103	0.043	0.247	0.177	0.175	0.399	0.307	0.298
	20-22	0.233	0.055	0.239	0.184	0.184	0.386	0.301	0.302
	23-24	0.209	0.079	0.421	0.370	0.347	0.642	0.593	0.558
	25-27	0.104	0.023	0.095	0.010	0.008	0.225	0.099	0.089
12	18-19	0.163	0.073	0.249	0.182	0.166	0.400	0.302	0.275
	20-22	0.334	0.106	0.328	0.262	0.243	0.527	0.440	0.412
	23-24	0.364	0.103	0.403	0.324	0.308	0.603	0.501	0.491
	25-27	0.750	0.114	0.476	0.361	0.346	0.686	0.531	0.510
13-15	20-22	0.077	0.030	0.149	0.118	0.103	0.264	0.228	0.220
	23-24	0.317	0.066	0.197	0.162	0.149	0.481	0.402	0.375
	25-27	0.463	0.063	0.113	0.100	0.090	0.356	0.316	0.293
16	23-24	0.208	0.055	0.098	0.064	0.068	0.044	0.050	0.055
	25-27	0.257	0.065	0.137	0.060	0.074	0.192	0.116	0.137

TABLE 4.4-M

Measures of Unemployment Insurance Utilization by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
			Measure			Measure		
	WR/WN	WR/WU	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
1979	0.366	0.855	0.595	0.509	0.492	0.677	0.597	0.579
1980	0.448	0.974	0.686	0.598	0.572	0.777	0.695	0.666
1981	0.376	0.875	0.609	0.525	0.500	0.677	0.600	0.572
1982	0.412	0.891	0.694	0.600	0.577	0.787	0.690	0.663
1983	0.366	0.835	0.675	0.591	0.562	0.738	0.649	0.615
1984	0.306	0.805	0.665	0.544	0.513	0.706	0.580	0.547
Average	0.379	0.874	0.654	0.561	0.536	0.727	0.635	0.607

TABLE 4.4-W

Measures of Unemployment Insurance Utilization by Year

(Measured as deviations from the mean for a 25 year old with 12 years of education)

Year	Measure		Broad Definition of Eligiblity			Narrow Definition of Eligibility		
			Measure			Measure		
	WR/WN	WR/WU	R/E	WR/WE	AR/AE	R/E	WR/WE	AR/AE
1979	0.094	0.711	0.372	0.268	0.266	0.633	0.488	0.483
1980	0.117	0.775	0.438	0.326	0.315	0.659	0.501	0.492
1981	0.109	0.744	0.432	0.316	0.302	0.683	0.512	0.492
1982	0.126	0.766	0.473	0.349	0.332	0.742	0.564	0.536
1983	0.124	0.806	0.526	0.428	0.399	0.698	0.581	0.546
1984	0.113	0.698	0.615	0.478	0.461	0.701	0.532	0.511
Average	0.114	0.750	0.476	0.361	0.346	0.686	0.531	0.510

tion group where there is no apparent relationship between the insured rate and age. Not surprisingly, women have lower rates than men.

Examining the other measures of utilization does not change the story for men in terms of the influence of demographic variables on UI use, but it does cloud the picture for women. For these other quantities, the positive relationship between age and utilization is now the exception rather than the rule.

According to the findings in Tables 4.4–M and 4.4–W, the nature of the time trends characterizing utilization depend on the measure choosen as a guide. For men, the fraction of insured unemployment follows a downward path starting in 1980, but the other measures accounting for eligibility based on either definition show essentially no trend. For women, on the other hand, there is no apparent time pattern conveyed by either the fraction of insured unemployment or the other measures of UI utilization based on the narrow definition of eligibility. However, the quantities based on the broad definition indicate a strong upward trend in UI utilization among women over the period covered.

4.6 *Comparison with Findings in the Literature*

Several recent studies provide a valuable context for interpreting and evaluating the results presented above. The studies of Burtless (1983), Burtless and Saks (1984), Corson and Nicholson (1988) and Blank and Card (1988) examine trends in insured, eligible and total unemployment covering the 1980's. While data limitations did not permit examination of all of the measures of eligibility and utilization analyzed here, these studies document a number of important patterns that serve as useful guides for identifying whether the experiences of youths are representative of the average unemployed worker.

The most frequently cited measure used to examine the utilization of the UI system is the proportion of the unemployed receiving regular UI benefits.[8] An examination of this measure over the last 50 years shows a general downward trend beginning in the early 1960's with a sharp downturn beginning in 1981. For example, during the 1940's and 1950's the

[8] This measure does not count individuals receiving extended benefits or workers covered under special UI programs as UI recipients. The special programs are the Unemployment Compensation for Federal Employees (UCFE), Unemployment Compensation for Ex-servicemember (UCX) and the Railroad Unemployment Insurance program. While individuals who file claims under the UCFE or UCX program must satisfy the same set of qualification requirements as other claimants, they are not eligible for regular UI.

ratio was approximately 0.50, it declined to 0.44 in the 1960's, fell to 0.40 over the 1970's, and during the 1980's it ranged from 0.44 in 1980 to 0.30 in 1984. While one can attribute the gradual decline throughout the 60's and 70's to variations in the demographic and industrial composition of the unemployed, the recent drop in the fraction of insured unemployment is somewhat unexplained. All the studies just cited associate at least half of the decline in the 1980's to unobserved changes either in the propensity of individuals to collect entitlements or in State administrative practices.

Another measure of UI utilization examined by Corson and Nicholson (1988) and Blank and Card (1988) is the ratio of the average weekly number of UI recipients under all programs to the total number of unemployed. This quantity displays a similar time pattern to the more restrictive measure above, except a slightly steeper decline is observed in the 1980's. Specifically, this ratio dropped from a value of 0.51 in 1980 to 0.34 in 1984 (Corson and Nicholson (1988) p. 9). Almost all of this drop-off appears to arise from changes in Federal policies relating to extended benefit programs and the reduction in the receipt of regular UI benefits.[9]

Blank and Card (1988) further examine the relationships between eligible unemployment and total or insured unemployment. One measure that Blank and Card investigate is the proportion of the unemployed eligible to receive UI benefits under all programs. Using earnings information from a previous year available in the March CPS to infer an unemployed individual's eligibility to receive UI, they find that the fraction of eligible unemployment remains roughly constant over the 1980's ranging from 0.50 in 1980 to 0.40 in 1984. Concerning the relationship between insured and eligible unemployment, Blank and Card explore the pattern of the take-up rate defined as the ratio of insured to eligible unemployment. Combining CPS data with administrative data on the number of UI recipients, they conclude that there was a significant decrease in the take-up rate over the 1980's.[10]

[9] In 1981 the U.S. Congress tightened the eligibility standards for extended benefits, eliminated the national insured unemployment rate trigger for extended benefits and increased the State trigger rate by 1 percent. In addition, the Federal Supplemental Benefit program that was enacted in response to the recession in 1982 was not as generous as the Federal Supplemental Compensation program enacted during the 1974–75 recession.

[10] Conversely, a sample of unemployment spells from the Panel Study of Income Dynamics analysed by Blank and Card show increasing take-up rates from 1980 through 1982.

With regard to relating our findings on the patterns of UI utilization to those in the literature, there is considerable agreement. Comparing the aggregate trends presented in Corson and Nicholson (1988) and Blank and Card (1988) with our results reported in Tables 4.4 indicates that the experiences of young workers in the 1980's are fairly representative of the population at large. This is especially true for the measures based on administrative data. For example, comparing the measure WR/WU from Table 4.4–M with the fraction of insured unemployment under all UI programs in Corson and Nicholson reveals striking similarities. While the magnitude of our utilization measure is significantly higher because it describes the behavior of what is essentially a young prime-age male, the time patterns are almost identical. From 1980 to 1984 both the aggregate measure and our value declined by 17 basis points i.e., 0.51 to 0.34 and 0.974 to 0.805 respectively.

On the other hand, our findings based on imputed measures of UI eligibility convey different patterns than those put forward in other work. Specifically, Blank and Card find decreasing take-up rates and relatively constant measures of the fraction of eligible unemployment, while the WR/WE and WE/WU measures in Tables 4.4 and 4.2 exhibit just the opposite patterns. Further research is needed to reconcile these disparities.

5. A General Estimation Approach

This section considers several issues relevant in designing an empirical model that enables one to measure the influence of UI policies on the duration of unemployment. The following analysis not only provides a basis for the subsequent empirical work, it also offers a useful framework for integrating and evaluating other empirical findings in the literature.

5.1 *Alternative Estimation Schemes*

To characterize the various procedures for analyzing the amount of unemployment experienced by individuals over some time horizon, the discussion below relies on the following definitions:

$$
\begin{aligned}
U &= \text{ weeks of unemployment;} \\
R &= (B, T) = \text{ UI policy regime;} \\
B &= \text{ rules of a UI program that define individuals' UI entitlements;} \\
T &= \text{ rules of a UI program that determine the taxation scheme used} \\
&\qquad\qquad \text{to finance the program;} \\
E &= \text{ UI entitlement variables;} \\
H &= \text{ work history;} \\
\delta &= \text{ indicator of UI receipt;} \\
Z &= \text{ demographic characteristics;} \\
M &= \text{ macroeconomic variables;} \\
PA &= \text{ population attributes consisting of elements in } H, Z \text{ and } M; \text{ and} \\
f(w|X) &= \text{ density or probability function of the variables } w \\
&\qquad\qquad \text{conditioning on the variables } X.
\end{aligned}
\tag{5.1}
$$

Attaching a subscript "i" to a variable designates the i^{th} observation of this variable. An observation refers to a variety of potential occurrences of unemployment. Thus, one may specify U_i to measure the number of weeks of unemployment that occurs in a spell of unemployment, or the total number of weeks of unemployment occuring within either a nonemployment spell or some fixed time interval. The variable R_i designates the rules of the UI program applicable

when U_i occurs. The T component of R encompasses such features as the experience-ratings relevant for firms in making their contributions into the UI system, and the B component of R determines the values of E assigned to individuals according to their work experiences H. The variables E_i include the weekly benefit amount and the number of weeks of UI eligibility that an individual qualifies for who experiences U_i. The attributes H_i summarize various dimensions of the individual's past work experience when U_i occurs. The indicator variable δ_i equals 1 if the individual experiencing U_i collects UI benefits and equals 0 otherwise. The variables Z_i provide information on the demographic characteristics of the person at the time of U_i, and M_i incorporates variables capturing exogenous macroeconomic determinants of unemployment durations.

Knowledge of the distribution $f(U|R, PA)$ for a judicious choice of the conditioning variables PA provides the principal information needed to assess the consequences of changing aspects of UI programs on the extent and the composition of unemployment. Inclusion of the variables Z among the covariantes PA specifies a distribution for a particular demographic group; inclusion of H in PA determines a distribution for various worker types; and incorporating M in PA admits adjustments for macroeconomic conditions. Fitting the distribution $f(U|R, PA)$ determines how U varies as one alters policy instruments incorporated in R for a population characterized by the attributes making up the covariates PA.

Estimating $f(U|R, PA)$ is not an easy task for two reasons. First, there is no simple way to quantify R. Programs differ quite substantially in their rules for determining individuals' weekly benefits and weeks of eligibility, and these rules are not readily summarized by a set of explanatory variables that vary along some continuous spectrum. Second, estimating the effects of R on the distribution of unemployment requires one to hold a population's composition constant as one varies the value of R. The primary source of variation in R arises from differences in UI policies across states. Recognizing that the characteristics of states' populations also differ, one typically encounters a situation in which shifts in the policy parameters R occur simultaneously with changes in population composition. Not accounting for these composition changes results in invalid inferences about the influence of R. As a consequence of the difficulties involved in obtaining a direct estimate of $f(U|R, PA)$,

empirical research on the effects of UI on unemployment utilizes other estimation approaches.

Specifically, this research tends to focus on estimating some variant of the distributions: $f(U|\delta = 1, E, PA)$, $f(U|\delta, PA)$, and $f(U|E, PA)$. Studies analyzing program data from State UI offices (e.g. Moffitt (1985), Meyer (1988), Katz and Meyer (1988a, 1988b)) estimate a specification of $f(U|\delta = 1, E, PA)$, which corresponds to the distribution describing the duration of unemployment for a UI recipient who qualifies for UI entitlements E and who comes from a population and an environment characterized by the attributes PA — in such analyses U measures number of weeks of UI receipt. Studies using survey data from such sources as the CPS, PSID or NLS estimate variants of $f(U|\delta, PA)$ and $f(U|E, PA)$. Empirical analyses comparing the hazard rates of UI recipients and non-UI recipients (e.g. Katz (1986) and Katz and Meyer (1988b)) in essence explore differences in the distribution $f(U|\delta, PA)$ when $\delta = 1$ and $\delta = 0$. Other work concerned with predicting the effects of UI entitlements on unemployment (e.g., Clark and Summers (1982a) and Topel (1983, 1985)) rely on some specification of $f(U|E, PA)$ as the basis for their estimation.

5.2 *Assessing the Influence of UI on Unemployment*

A key question that has gone unanswered in the literature concerns what can be learned about the distribution $f(U|R, PA)$ from estimated variants of the densities $f(U|\delta = 1, E, PA)$, $f(U|\delta, PA)$ and $f(U|E, PA)$. In particular, if one finds that higher UI entitlements E imply a shift in these distributions of U indicating greater unemployment, can one conclude, as is typically done in the literature, that a more generous UI policy regime will lead to more unemployment? The answer to this question is no unless one incorporates the appropriate measures of work history variables H to serve as controls among the covariates PA.

To ensure that estimated effects associated with UI entitlement variables have the interpretation typically given to them in the literature, the variation in E admitted in empirical specifications must reflect purely differences in policy regimes. While UI programs differ quite substantially in terms of the rules they apply to determine benefits, all programs define benefits using information on only a few aspects of a person's recent work history. As outlined in Section 2.1, these aspects include such items as base period earnings (BPE), high quarter earnings (HQE), average weekly earnings (AWE), the circumstances under

which employment terminated (e.g. quit, fire, etc.), and whether previous employment was covered by the UI system. Incorporating these items among the work history variables H, there essentially exists a functional relationship linking H and a UI policy regime R to UI entitlements E. In particular, one can specify functions of the form

$$E = \Phi(H, M, R) = \Phi(H, M, B), \tag{5.2}$$

which show how a person's UI weekly benefit amount and weeks of eligibility are assigned given this individual's past work experiences and the rules of the UI program. The inclusion of the macroeconomic variables M as arguments of the function Φ accounts for the fact that some program features such as extended benefits depend on the levels of state unemployment rates. The second expression for Φ given in (5.2) recognizes that only the B component of R determines the entitlements of a system.

In estimation, the only source of variation in E of interest for drawing inferences about the influence of UI policies operates through the regime variables R or B. Inspection of the functions Φ highlight the point that E varies across observations in a sample not only due to shifts in R, but also as a consequence of differences in the work histories of individuals and possibly due to changes in value of M either across states or over time. If one incorporates the group of work history and macroeconomic variables included in H and M appearing in (5.2) as elements of the conditioning variables PA in the distributions $f(U|\delta, E, PA)$ or $f(U|E, PA)$, then all variation in E may be attributed to differences in the generosity of UI systems. Under such circumstances, one can interpret estimated effects associated with entitlements as reflecting responses to varying the characteristics of UI policy. These policy shifts arise as the consequence of considering individuals covered by different state programs or as the result of changes in UI policy over time.

The importance of including work history variables among the covariates to obtain reliable estimates of entitlement effects has long been recognized in the empirical literature on UI and unemployment. Surveys of this topic (e.g. Welch (1977), Hamermesh (1977) and Danziger, Haverman and Plotnick (1981)) discuss a variety of possible biases that might be present as a consequence of not capturing the appropriate source of variation in the variables E. However, while virtually all empirical studies account for some measure of H in their

analyses, none of which we are aware includes the specification of controls needed in theory to purge E of variability other than that due to shifts in R.*

One finds a variety of work history variables incorporated in empirical analyses of UI effects. The most popular choice for H consists of a single measure of an individual's average weekly earnings (AWE). Researchers typically enter AWE through some representation of a "wage replacement ratio", and quite often AWE is introduced in an after-tax form to capture the notion of opportunity cost more accurately. All UI systems use many work history variables in addition to AWE to determine benefits. Consequently, a specification of H consisting of only AWE is incomplete. The use of an after-tax form of AWE is likely to introduce even more serious sources of bias in estimation because UI benefits are based on the before-tax values of AWE rather than on after-tax quantities. It is not uncommon to find empirical studies incorporating many work history variables other than AWE in their analysis – including such quantities as base period or high quarter earnings which actually go into the determination of entitlements – but we know of no attempt to account for the full complement of variables and interactions needed to characterize the benefit structure of UI programs. Without accounting for this structure, UI entitlement and receipt variables E and δ in part perform the task of identifying worker types, with higher values of E and δ signifying those types who experience more unemployment. Such an occurrence in principle leads to incorrect inferences about the role of these variables as determinants of unemployment. Of course, the inclusion of only a subset of the relevant work history variables may be sufficient to avoid any serious biases in estimation.

5.3 *Measuring the Impact of Shifts in UI Policy*

Predicting comprehensive effects of UI policies on unemployment requires some formulation of the distribution $f(U|R, PA)$. As noted above, the direct estimation of this quantity involves a number of complications. A more attractive approach for constructing $f(U|R, PA)$ consists of combining information on estimated variants of $f(U|\delta, E, PA)$, and $f(\delta|E, PA)$, which represent the types of distributions analyzed in the literature. The distribution $f(U|\delta, E, PA)$ indicates the extent to which unemployment differs across UI and non-UI recipient populations according to levels of UI entitlements. The divergence between

$f(U|\delta = 1, E, PA)$ and $f(U|\delta = 0, E, PA)$ offers a measure of the shift in unemployment attributable to participation in UI programs. The second distribution $f(\delta|E, PA)$ determines the probability that individuals characterized by attributes PA become UI recipients when facing values of entitlements equal to E. Even if the difference in unemployment between UI and non-UI recipients is small, a modification in a UI program could have a large effect if it results in a big adjustment in the probability of UI participation.

Developing the relationship that enables one to construct $f(U|R, PA)$ from these other distributions requires several steps. According to familiar results in statistics,

$$f(U|R, PA) = \sum_{\delta, E} f(U|\delta, E, R, PA)\, f(\delta|E, R, PA)\, f(E|R, PA). \tag{5.3}$$

The summation sign used here assumes that all distributions are discrete — if they were continuous an integral sign would be used instead — with the summations carried out over the admissible range of the variables δ and E. The right-hand-side of formula (5.3) merely represents the joint distribution of the variables U, δ and E conditional on R and PA, with all the variables other than U integrated out.

A substantial simplification occurs in this representation of $f(U|R, PA)$ if one fully exploits the linkage relating entitlements, work history and policy regimes conveyed by the functions (5.2). According to these functions, as long as one includes sufficient information in H, the functional relationship linking E, H, M and B given by (5.2) means that knowledge of E and H eliminates the need to know B. This observation allows one to simplify or to avoid estimating the distributions appearing in formula (5.3). With respect to the first two distributions, one obtains

$$\begin{aligned} f(U|\delta, E, R, PA) &= f(U|\delta, E, T, PA) \\ f(\delta|E, R, PA) &= f(\delta|E, T, PA). \end{aligned} \tag{5.4}$$

One can eliminate B as conditioning variables because E, H and M implicitly summarize all the essential information in B. The ability to ignore B in specifying these distributions substantially reduces the problem of estimating them because one need not tackle the difficult task of quantifying B. Concerning the third distribution, $f(E|R, PA)$, appearing in formula (5.3), there is not even a need to estimate this quantity. Knowledge of H and R determines

E exactly. Alternatively, one can express this result as

$$f(E|R, PA) = \Phi(H, M, R) \tag{5.5}$$

where the function Φ is given by (5.2).

Combining these results, provides the relationship that permits construction of $f(U|R, PA)$ from distributions that are more readily analyzed in empirical work. Substituting (5.4)–(5.5) into (5.3) yields

$$f(U|R, PA) = \sum_{\delta, E} f(U|\delta, E, T, PA)\, f(\delta|E, T, PA)\, \Phi(H, M, R). \tag{5.6}$$

One can estimate specifications of the distributions $f(U|\delta, E, T, PA)$ and $f(\delta|E, T, PA)$ using micro data. The functions Φ are known depending on the UI policy under consideration. Formula (5.6) shows how to combine these quantities to compute an estimate of $f(U|R, PA)$.

5.4 *An Alternative Formulation*

When the variable U measures the accumulative number of weeks of unemployment that occur over some period of time – which is the type of measure analyzed in the subsequent empirical work – it is not convenient for estimation purposes to work directly with a parameterization of the distribution $f(U|\delta, E, T, PA)$ appearing in formula (5.6). If one presumes that a standard duration model describes spells of unemployment and spells in other labor market activities as well, then the implied specification for distribution of U (i.e., of total weeks of unemployment over a time horizon) is quite complex.

To avoid such complexities in developing a specification for the distribution $f(U|\delta, E, T, PA)$, an attractive alternative involves decomposing U into two components and specifying the distributions for these separate components. In particular, define $U = \rho\ell$ where ℓ = the length of the relevant time horizon over which total nonemployment is measured, and ρ = the fraction of ℓ classified as unemployment. From the two conditional distributions $f(\ell|\delta, E, T, PA)$ and $f(\rho|\ell, \delta, E, T, PA)$, one can infer the distribution associated with U via the formula

$$f(U|\delta, E, T, PA) = \sum_{\ell=1}^{\infty} \sum_{\rho=U/\ell} f(\rho|\ell, \delta, E, T, PA)\, f(\ell|\delta, E, T, PA). \tag{5.7}$$

The quantity $f(\ell|\delta, E, T, PA)$ represents a conventional duration distribution that describes the spell length ℓ; and we refer to $f(\rho|\ell, \delta, E, T, PA)$ as a time-proportion distribution because it characterizes the portion of a duration ℓ spent in a particular status.

6. A Specification Characterizing the Duration of Unemployment Between Jobs

The central question addressed in the subsequent empirical analysis is the following: Given the onset of nonemployment (i.e. the initiation of a nonemployment spell), what is the relationship between UI entitlements and the accumulative amount of unemployment that an individual experiences before he or she returns to employment? To answer this question within the framework presented in the previous section, one can interpret the variable U as the total number of weeks of unemployment that an individual reports during a spell of nonemployment, with observations on U available for a random sample of nonemployment episodes; the variable ℓ corresponds to the length of these nonemployment spells measured in weeks; and the fraction ρ represents the proportion of a nonemployment spell reported as unemployment.

While knowledge of the distribution $f(U|R, PA)$ formulated in the following analysis to answer the question posed above provides much of what is needed to predict many of the combined effects of UI programs, it falls short of supplying all that is required to evaluate the total effects of UI policies on unemployment. Because work-history variables make up a part of the conditioning elements PA, $f(U|R, PA)$ ignores the potential influence of UI on the initiation of nonemployment episodes or on any other aspect of work or earnings activities. Consequently, the empirical framework developed below is essentially conditional in spirit in that it estimates the amount unemployment experienced by individuals who are known to have just left employment with recent work records of a particular nature. Thus, the estimated effects presented below represent the total effects of UI policies only if one is willing to presume that the influence of UI programs on employment experiences is negligible. If one does not accept such a presumption, then carrying out the conditional analysis considered here is a necessary step in the development of a complete description of the influence of UI programs on unemployment. Pursuing a framework capable of predicting the full impact of UI policies requires one to combine the sort of analysis considered in this paper with a model of the effects of UI policies on the employment-nonemployment decision

and on earnings.[11]

6.1 *A Sample Linking UI Entitlements and Unemployment Durations*

To construct reliable measures of a youth's UI entitlements and receipt of benefits, this paper analyzes a subsample of 3028 individuals drawn from the randomly chosen nationally representative sample of 6,111 youths in the YNLS. A detailed description of the sample selection criteria is presented in Appendix B. In short, inclusion in the subsample required a youth to meet the following 5 conditions: (1) interviewed in each of the first 7 years; (2) worked at least once since January 1979; (3) have valid beginning and ending dates for time periods spent employed, between jobs and in the military; (4) left school and did not return prior to the 1985 interview date; and (5) have a reasonably accurate and complete time series of weekly earnings beginning with January 1978 or the last date of school attendance. The subsample contains 1409 men and 1619 women who experience 4031 and 4250 episodes of nonemployment respectively.

Summary statistics of nonemployment spells and the demographic characteristics of individuals at the beginning of spells are presented in Table 6.1-M for men and in Table 6.1-W for women. Each table reports results for nonemployment spells divided into three distinct groups: the top group presents statistics for spells in which an individual is not eligible to receive UI benefits; the middle group summarizes the characteristics of spells in which a youth is eligible to receive UI payments but fails to do so; and the lower group describes spells associated with the receipt of UI benefits at some time during the nonemployment episode.[12] A casual examination of these summary statistics indicates that UI recipients are slightly older, are more likely to be on layoff, and experience more unemployment.

Tables 6.2–M and 6.2–W present summary statistics of the work history variables that enter into the determination of persons' UI entitlements as well as the imputed measures of UI benefits obtained for the eligible youths in the YNLS, using the broad definition of

[11] In particular, one needs to develop and estimate a specification a distribution of the form $f(PA|R)$ or $f(PA|R, Z)$ which determines how work-history variables H vary across different policy regimes. For the analysis presented here, H not only incorporates all of the aspects of earnings that go into the determination of UI benefits, it also implicitly contains information signifying the termination of employment in the immediate past.

[12] Note, the same individual may be associated with all three spell catagories.

TABLE 6.1-M

Summary Statistics of Demographics and Nonemployment Spells for Males
Number of Individuals in Sample = 1409

Variable	Mean	Std.Dev.	Min.	25%	50%	75%	Max.
Spells for which individual is not eligible for UI: number of spells = 2122							
Age	20.94	2.36	15.0	19.0	21.0	22.0	27.0
Years of Education	11.77	2.06	7.0	11.0	12.0	12.0	19.0
Percent Non-White	0.21						
Spell Length	16.01	26.39	1.0	3.0	6.0	19.0	337.0
Weeks of Unemployment	6.86	15.32	0.0	0.0	1.0	7.0	259.0
Percent of Spell Unemployed	0.39	0.45	0.0	0.0	0.1	1.0	1.0
Fraction Entirely OLF	0.47						
Fraction entirely UE	0.30						
Fraction on Layoff	0.12						
Fraction returning to original Employer	0.30						
Spells for eligible nonrecipients: number of spells = 1190							
Age	20.73	2.28	16.0	19.0	20.0	22.0	28.0
Years of Education	11.55	1.77	7.0	11.0	12.0	12.0	18.0
Percent Non-White	0.21						
Spell Length	12.95	19.76	1.0	2.0	5.0	14.0	172.0
Weeks of Unemployment	7.59	13.06	0.0	1.0	3.0	8.0	126.0
Percent of Spell Unemployed	0.64	0.43	0.0	0.1	1.0	1.0	1.0
Fraction Entirely OLF	0.23						
Fraction entirely UE	0.53						
Fraction on Layoff	0.42						
Fraction returning to original Employer	0.24						
Spells for UI recipients: number of spells = 719							
Age	21.99	2.25	17.0	20.0	22.0	24.0	28.0
Years of Education	11.61	1.47	7.0	12.0	12.0	12.0	18.0
Percent Non-White	0.13						
Spell Langth	17.66	22.42	1.0	4.0	10.0	22.0	239.0
Weeks of Unemployment	14.59	17.63	1.0	3.0	9.0	19.0	216.0
Percent of Spell Unemployed	0.87	0.28	0.1	1.0	1.0	1.0	1.0
Fraction Entirely OLF	0.00						
Fraction entirely UE	0.79						
Fraction on Layoff	0.73						
Fraction returning to original Employer	0.40						

TABLE 6.1-W

Summary Statistics of Demographics and Nonemployment Spells for Females
Number of Individuals in Sample = 1619

Variable	Mean	Std.Dev.	Min.	25%	50%	75%	Max.
Spells for which individual is not eligible for UI: number of spells = 2924							
Age	21.18	2.46	15.0	19.0	21.0	23.0	27.0
Years of Education	12.03	1.92	7.0	12.0	12.0	13.0	18.0
Percent Non-White	0.18						
Spell Length	29.07	48.44	1.0	3.0	10.0	33.0	330.0
Weeks of Unemployment	5.15	12.72	0.0	0.0	0.0	4.0	139.0
Percent of Spell Unemployed	0.25	0.38	0.0	0.0	0.0	0.5	1.0
Fraction Entirely OLF	0.55						
Fraction entirely UE	0.16						
Fraction on Layoff	0.08						
Fraction returning to original Employer	0.30						
Spells for eligible nonrecipients: number of spells = 906							
Age	20.82	2.24	16.0	19.0	21.0	22.0	27.0
Years of Education	12.02	1.94	7.0	12.0	12.0	12.0	18.0
Percent Non-White	0.12						
Spell Length	22.21	38.82	1.0	3.0	8.0	20.0	289.0
Weeks of Unemployment	5.54	11.02	0.0	0.0	2.0	6.0	137.0
Percent of Spell Unemployed	0.47	0.44	0.0	0.0	0.3	1.0	1.0
Fraction Entirely OLF	0.33						
Fraction entirely UE	0.36						
Fraction on Layoff	0.24						
Fraction returning to original Employer	0.19						
Spells for UI recipients: number of spells = 420							
Age	21.75	2.25	17.0	20.0	22.0	23.0	27.0
Years of Education	11.88	1.46	7.0	12.0	12.0	12.0	18.0
Percent Non-White	0.11						
Spell Length	26.37	39.04	1.0	5.0	12.0	32.0	297.0
Weeks of Unemployment	13.43	17.98	1.0	2.0	7.0	18.0	115.0
Percent of Spell Unemployed	0.72	0.39	0.1	0.4	1.0	1.0	1.0
Fraction Entirely OLF	0.00						
Fraction entirely UE	0.60						
Fraction on Layoff	0.56						
Fraction returning to original Employer	0.32						

TABLE 6.2-M

Summary Statistics of Work History and UI Entitlements for Males
Number of Individuals in Sample = 1409

Variable	Mean	Std.Dev.	Min.	25%	50%	75%	Max.
Spells for which individual is not eligible for UI: number of spells = 2122							
Base Period Earnings	4890	5780	0	640	2760	7200	54600
High Quarter Earnings	1890	1780	0	500	1610	2730	21990
Average Weekly Earnings	157	212	0	58	136	211	949
Weeks of Work	24.92	19.45	0.00	7.00	21.00	46.00	52.00
Ratio of Base Period to High Quarter Earnings	1.91	1.24	0.00	1.00	1.77	2.96	4.00
Fraction Satisfying Earnings Requirement	0.53						
Spells for eligible nonrecipients: number of spells = 1190							
Base Period Earnings	7380	5080	380	3680	6190	9680	37940
High Quarter Earnings	2610	1580	190	1510	2280	3250	16100
Average Weekly Earnings	188	199	20	113	160	229	1090
Weeks of Work	38.88	12.69	7.00	29.00	42.00	51.00	52.00
Ratio of Base Period to High Quarter Earnings	2.78	0.78	1.05	2.14	2.84	3.44	4.00
Weekly Benefit Amount	81.60	40.97	10.00	48.00	76.00	108.00	221.00
Weeks of Eligibility	23.24	6.23	1.00	19.00	26.00	26.00	55.00
Fraction Who Meet Stricter Eligiblity Condition	0.58						
Spells for UI recipients: number of spells = 719							
Base Period Earnings	11090	7040	2100	6470	9800	14480	54590
High Quarter Earnings	3580	2120	1240	2210	3250	4420	21990
Average Weekly Earnings	260	148	93	164	234	327	1331
Weeks of Work	41.06	13.69	12.00	34.00	47.00	52.00	52.00
Ratio of Base Period to High Quarter Earnings	2.98	0.90	1.30	2.41	3.24	3.72	4.00
Weekly Benefit Amount	98.52	49.99	25.00	68.00	97.00	134.00	223.00
Weeks of Eligibility	22.22	9.76	1.00	20.00	26.00	26.00	55.00
Fraction of Second Spells in Benefit Year	0.22						

TABLE 6.2-W

Summary Statistics of Work History and UI Entitlements for Females
Number of Individuals in Sample = 1619

Variable	Mean	Std.Dev.	Min.	25%	50%	75%	Max.
Spells for which individual is not eligible for UI: number of spells = 2924							
Base Period Earnings	3630	4300	0	270	2030	5650	32260
High Quarter Earnings	1380	1340	0	220	1150	2080	11580
Average Weekly Earnings	108	93	0	33	100	157	768
Weeks of Work	24.59	19.97	0.00	5.00	21.00	46.00	52.00
Ratio of Base Period to High Quarter Earnings	1.85	1.30	0.00	1.00	1.72	3.02	4.00
Fraction Satisfying Earnings Requirement	0.54						
Spells for eligible nonrecipients: number of spells = 906							
Base Period Earnings	5690	3590	300	2920	4840	7570	27010
High Quarter Earnings	2030	1120	220	1280	1810	2590	9880
Average Weekly Earnings	142	75	17	93	129	180	519
Weeks of Work	39.34	11.88	6.00	30.00	42.00	51.00	52.00
Ratio of Base Period to High Quarter Earnings	2.75	0.78	1.06	2.09	2.77	3.45	4.00
Weekly Benefit Amount	69.37	36.15	10.00	41.00	63.00	90.00	196.00
Weeks of Eligibility	22.93	6.24	1.00	19.00	26.00	26.00	50.00
Fraction Who Meet Stricter Eligiblity Condition	0.39						
Spells for UI recipients: number of spells = 420							
Base Period Earnings	7450	3750	150	4820	7310	9580	21770
High Quarter Earnings	2480	1190	150	1770	2300	2920	8930
Average Weekly Earnings	172	81	20	126	160	206	1011
Weeks of Work	42.45	12.33	13.00	34.00	49.00	52.00	52.00
Ratio of Base Period to High Quarter Earnings	2.96	0.84	1.00	2.40	3.08	3.69	4.00
Weekly Benefit Amount	81.70	39.36	10.00	58.00	78.00	102.00	197.00
Weeks of Eligibility	22.92	8.49	1.00	20.00	26.00	26.00	50.00
Fraction of Second Spells in Benefit Year	0.19						

eligibility discussed in Section 4. In keeping with the format of the previous tables, Tables 6.2-M and 6.2-W divide nonemployment spells into three distinct groups determined by the eligibility and recipiency status of youths during each nonemployment spell they experience. As expected, both the work history variables and the UI entitlement variables increase as one moves down the groupings.

6.2 *Defining Variables in the Empirical Specifications*

Applying the framework presented in Section 5 to investigate the question posed above requires choices for all variables appearing in formula (5.6), which includes U, δ, Z, E, H, M and T. With U representing accumulative unemployment between jobs, the indicator variable δ signifies whether an individual is a UI recipient during the relevant spell of nonemployment, taking a value of 1 if the person collects UI benefits and a value of 0 otherwise. The demographic characteristics considered in the following empirical analysis include the variables

$$
(6.1) \quad Z : \begin{aligned}
\text{AGE} &= \text{age of an individual at the beginning of a} \\
&\quad\ \text{nonemployment spell;} \\
\text{EDU} &= \text{education of an individual at the beginning of a} \\
&\quad\ \text{nonemployment spell;} \\
\text{RACE} &= \text{dummy variable that takes a value of 1 if an individual's} \\
&\quad\ \text{race is non-caucasian;} \\
\text{MARRIED} &= \text{dummy variable that takes a value of 1 if an individual is} \\
&\quad\ \text{married at the beginning of a nonemployment spell;} \\
\text{NUMKIDS} &= \text{the number of children in household at the beginning} \\
&\quad\ \text{of a nonemployment spell; and} \\
\text{Gender} &= \text{sex of individual.}
\end{aligned}
$$

This leaves the variables E, H, M and T whose specification must capture the structural features of UI programs.

As noted in Section 5, the relationships linking UI entitlements and work-history variables

are quite intricate. The two variables comprising UI entitlements are

$$(6.2) \qquad E \; : \; \begin{aligned} WBA &= \text{weekly benefit amount; and} \\ WE &= \text{weeks of eligibility.} \end{aligned}$$

The determination of these entitlements depends on an individual's work-history variables

$$(6.3) \qquad H \; : \; \begin{aligned} AWE &= \text{average weekly earnings;} \\ BPE &= \text{base period earnings;} \\ HQE &= \text{high quarter earnings; and} \\ PQ &= \text{1 if individual quit job for personal reasons or} \\ &\quad \text{without good cause, and } = 0 \text{ otherwise.} \end{aligned}$$

Besides $PQ = 0$, the values of the above earnings variables must fall into particular regions for individuals to qualify for benefits (i.e., for WBA and WE, to be nonzero).[13] Assuming eligibility, State UI systems use a variety of formulae relating the variables AWE, BPE and HQE to assign WBA and WE.[14] These formulae can depend on sophisticated interactions involving the various earnings measures, and all programs introduce nonlinearities through lower and upper thresholds in benefits. To capture these interactions and nonlinearities, the following empirical analysis introduces a set of dummy variables that designate which of a series of brackets contain the combination of AWE, BPE and HQE associated with an individual at the onset of a nonemployment spell.

Measures of WE used in the following empirical analysis also take into account the availability of both extended benefits and supplemental unemployment compensation. Through the extended benefits program, in conjuction with the Federal Government, States provide up to 13 additional weeks of UI benefits during periods of unusually high state unemployment. In addition, from September 1981 through March 1985 an additional 8 to 16 weeks of UI benefits were available to individuals who qualified for extended benefits through the Federal Supplemental Compensation program. If either of these additional benefits were available to an individual during a nonemployment spell and he or she qualified for these

[13] In this analysis, recall that the fact that a person started a nonemployment spell is implicitly also a part of H, but it need not be made explicit in the empirical specification considered below.

[14] Note that programs using information on weeks worked in the base year (WW) are simply combining information on AWE and BPE since $WW = BPE/AWE$.

benefits, WE at the beginning of the spell is equal to the number of weeks of regular benefits available plus the appropriate number of weeks of extended and supplemental benefits.

The inclusion of extended benefits in the determination of UI entitlements means that macroeconomic variables in the form of the States' unemployment rates enter as arguments of the Φ functions given by (5.2). To account for this factor, and to control for the effects of aggregate economic conditions, the following empirical work incorporates the macroeconomic variables[15,16]

$$\begin{aligned} M : UNRATE &= \text{the unemployment rate of the state in which} \\ &\quad\ \text{an individual resides at the beginning of the} \\ &\quad\ \text{relevant nonemployment spell; and} \\ EBDUM &= \text{dummy variable that takes a value of 1 when extended} \\ &\quad\ \text{benefits apply in an individual's states of residency during} \\ &\quad\ \text{the relevant nonemployment spell.} \end{aligned} \tag{6.4}$$

Finally, the only quantity left unspecified is the variable T, which characterizes the taxation structure of UI systems in the financing of programs. To admit the possibility that such program features may have important consequences on the duration of unemployment between jobs, the subsequent empirical work considers only a single measure specified as

$$\begin{aligned} UITAX = &\ \text{average tax rate in a State's UI system in which an} \\ &\ \text{individual resides during the calendar year when a} \\ &\ \text{nonemployment spell begins.} \end{aligned} \tag{6.5}$$

The data used for $UITAX$ is the total amount of UI tax collections divided by the total amount of wages paid in covered employment in the relevant state and calendar year.[17] Admittedly, this variable can at best serve as only a very crude proxy for marginal tax rates faced by firms in a state, which are the rates relevant for assessing the overall UI subsidy

[15] In the subsequent empirical work, UNRATE is the unemployment rate for the state in question reported for the mid-month of the quarter closest to the start of the nonemployment spell. We obtained this data from the *Monthly Labor Review*.

[16] We are grateful to David Card for supplying us with the data on the variable $EBDUM$ which he originally obtained from the U.S. Department of Labor.

[17] The tax rate data is obtained from the annual issues of "Unemployment Insurance Financial Data" published by the U.S. Department of Labor.

due to incomplete experience ratings. Movements in average tax rates can to some extent capture shifts in UI tax schedules that occur as states adjust rates to cover outlays. It is these shifts that we hope to control with the inclusion of UITAX. This quantity, like those making up M, varies more across states than over time for the same state and, consequently, these quantities in part capture permanent state effects.

6.3 *Representative Cases*

To evaluate the implication of the distributions estimated below, the following discussion compares results for three representative worker types subject to four UI policy regimes which typify the structure of state programs. The cases considered here are prototypes of the data used in this paper to estimate UI effects.

The three worker types are:

$$\begin{array}{lllll} H_{\ell} : & AWE = \$100 & HQE = \$1000 & BPE = \$1500 & PQ = 0 \\ H_m : & AWE = \$200 & HQE = \$2000 & BPE = \$8000 & PQ = 0 \\ H_h : & AWE = \$500 & HQE = \$5000 & BPE = \$20000 & PQ = 0\,. \end{array} \tag{6.6}$$

Type H_{ℓ} is a low-intensity worker who earns \$100 a week for 15 weeks in the base year and 10 weeks in the high quarter; type H_m is a medium-intensity worker who earns \$200 a week for 40 weeks in the base year and 10 weeks in the high quarter; and type H_h is a high-intensity worker who earns \$500 a week for 40 weeks in the base year and for 10 weeks in the high quarter.

The four representative UI policy regimes considered below are:

$$
\begin{aligned}
&R_1 : \ \text{eligible if } BPE \geq HQE * 1.5 \ \text{ and } \ HQE \geq \$1000 \\
&\qquad \text{given eligible} : WBA = .5\ AWE \ \text{ up to a maximum of } \$150 \\
&\qquad\qquad\qquad\qquad WE = .27\ (BPE/WBA) \ \text{ up to a maximum of } 26 \\
&R_2 : \ \text{eligible if } BPE \geq HQE * 1.5 \ \text{ and } \ HQE \geq \$1000 \\
&\qquad \text{given eligible} : WBA = .5\ AWE \ \text{ up to a maximum of } \$200 \\
&\qquad\qquad\qquad\qquad WE = 26 \\
&R_3 : \ \text{eligible if } BPE \geq HQE * 1.5, \ HQE \geq \$1000 \ \text{ and } \ WW = BPE/AWE \geq 20 \\
&\qquad \text{given eligible} : WBA = .6\ AWE \ \text{ up to a maximum of } \$250 \\
&\qquad\qquad\qquad\qquad WE = 26 \\
&R_4 : \ \text{eligible if } BPE \geq HQE * 1.5, \ HQE \geq \$1000 \ \text{ and } \ WW = BPE/AWE \geq 20 \\
&\qquad \text{given eligible} : WBA = .6\ AWE \ \text{ up to a maximum of } \$250 \\
&\qquad\qquad\qquad\qquad WE = 39
\end{aligned}
\tag{6.7}
$$

Generally these policy regimes offer successfully higher WBA and WE. Regimes R_3 and R_4 impose a more stringent eligibility criteria since they add the restriction that an individual must work at least 20 weeks in the base year to the other threshold requirements on earnings. Under these various programs, the three persons with work histories designated by (6.6) are

assigned:

$$
\begin{array}{llllll}
\text{Worker type } H_\ell & : & \text{under } R_1 & : & WBA = 50\,, & WE = 8 \\
 & & R_2 & : & \quad\;\; = 50\,, & \quad\; = 26 \\
 & & R_3 & : & \quad\;\; = 0\,, & \quad\; = 0 \\
 & & R_4 & : & \quad\;\; = 0\,, & \quad\; = 0 \\
 & & & & & \\
\text{Worker type } H_m & : & \text{under } R_1 & : & WBA = 100\,, & WE = 20 \\
 & & R_2 & : & \quad\;\; = 100\,, & \quad\; = 26 \\
 & & R_3 & : & \quad\;\; = 120\,, & \quad\; = 26 \\
 & & R_4 & : & \quad\;\; = 120\,, & \quad\; = 39 \\
 & & & & & \\
\text{Worker type } H_h & : & \text{under } R_1 & : & WBA = 150\,, & WE = 26 \\
 & & R_2 & : & \quad\;\; = 200\,, & \quad\; = 26 \\
 & & R_3 & : & \quad\;\; = 250\,, & \quad\; = 26 \\
 & & R_4 & : & \quad\;\; = 250\,, & \quad\; = 39
\end{array}
\tag{6.8}
$$

Of course, all of these UI entitlement assignments presume that each individual in question did not quit his or her job for personal reasons or left employment under other circumstances that would result in disqualification.

7. The Influence of UI Programs on Nonemployment

This section describes the specification and the estimation of the duration distribution associated with the lengths of nonemployment spells, referred to as $f(\ell|\delta, E, T, PA)$ in the previous discussion. This type of distribution permits investigation of the effects of UI programs on the lengths of nonemployment spells, whereas the goal of most other work in this area has been to assess the effects of UI on unemployment spells. The implication of this analysis for durations of unemployment will be taken up in Section 10 where these results are combined with findings developed in the next two sections.

7.1 *Duration Distributions and Survivor Functions*

A duration distribution characterizes the likelihood that an individual experiences a particular number of weeks in a specific labor market status given initial entry into the status. A formulation for such a distribution is given by

$$(7.1) \qquad f(\ell|X) = S(\ell-1)\,[1 - P(X,\ell)]$$

with

$$(7.2) \qquad S(\ell-1) = \prod_{t=1}^{\ell-1} P(X,t)$$

where $P(X, t)$ represents a probability that conditions on the variables X and t. The function $f(\ell|X)$ specifies the probability that duration in a status will last exactly ℓ weeks for individuals falling into a category characterized by attributes X who are known to have entered the status at some time. The literature designates the quantity $S(\ell-1)$ as the survivor function; it indicates the probability that individuals in this category will experience at least $\ell - 1$ weeks in the status. For the problem of concern in this analysis, $f(\ell|X) = f(\ell|\delta, E, T, PA)$; that is ℓ corresponds to the duration of a nonemployment spell and the covariates X include all the variables incorporated in the attributes δ, E, T, H, Z and M.

In the specification of the probabilities $P(X, t)$, the variables X are set at the time of entry into the status, and the variable t represents the level of duration accumulated up to the point of evaluation. The literature terms the influence of t on P as duration dependence. If

$P(X, t)$ increases (decreases) as a function of t, then positive (negative) duration dependence is said to exist.

Proposing a specification for f and S requires the acquisition of some basic information concerning the appropriate functional form for the probabilites $P(X, t)$. Learning about two aspects of this functional form are critical prior to estimation. The first involves the nature of duration dependence applicable for the data under investigation, which primarily determines how P varies with t. The second concerns the possibility that the central features of duration dependence change as one alters the values of X. An indication of such a possibility means that one must admit an interaction between X and t in the specification of P to capture the underlying nature of the relationship.

7.2 *Exploratory Data Analysis*

Plotting hazard rates is a popular mode for presenting information about the character of duration dependence. A hazard rate is defined as follows:

$$H(\ell) = f(\ell)/S(\ell - 1) = 1 - P(X, \ell). \tag{7.3}$$

One can construct estimates of $H(\ell)$ for nonemployment spells by selecting a sample composed of all the separate observations on spell lengths associated with some value of the attributes X. Calculating the fraction of all spells that end in exactly ℓ weeks estimates $f(\ell)$, and computing the fraction of all spells that exceeds $\ell - 1$ weeks estimates $S(\ell - 1)$. Plotting $H(\ell)$ against ℓ indicates how $P(X, \ell)$ varies as a function of ℓ.

Figures 7.1–M and 7.1–W present graphs of empirical hazards for nonemployment spells;[18] the designation "M" indicates graphs for the sample of men and "W" signifies graphs for women. In this exploratory data exercise, the covariates X merely consist of the UI-receipt indicator variable δ. Each figure reports two plots: one for occurrences during which UI receipt took place at any time during the spell (i.e. for nonemployment spells associated with $X = \delta = 1$); and a second plot for occurrences in which no UI benefits are collected (i.e. when $X = \delta = 0$).

These figures reveal two important properties of duration dependence in nonemployment episodes. First, the probability P is not a monotonic function of t. It initially increases in

[18] The calculation of these hazards assumes two-week intervals.

FIGURE 7.1-M
Empirical Hazard Rates for Nonemployment Spells
By UI Status

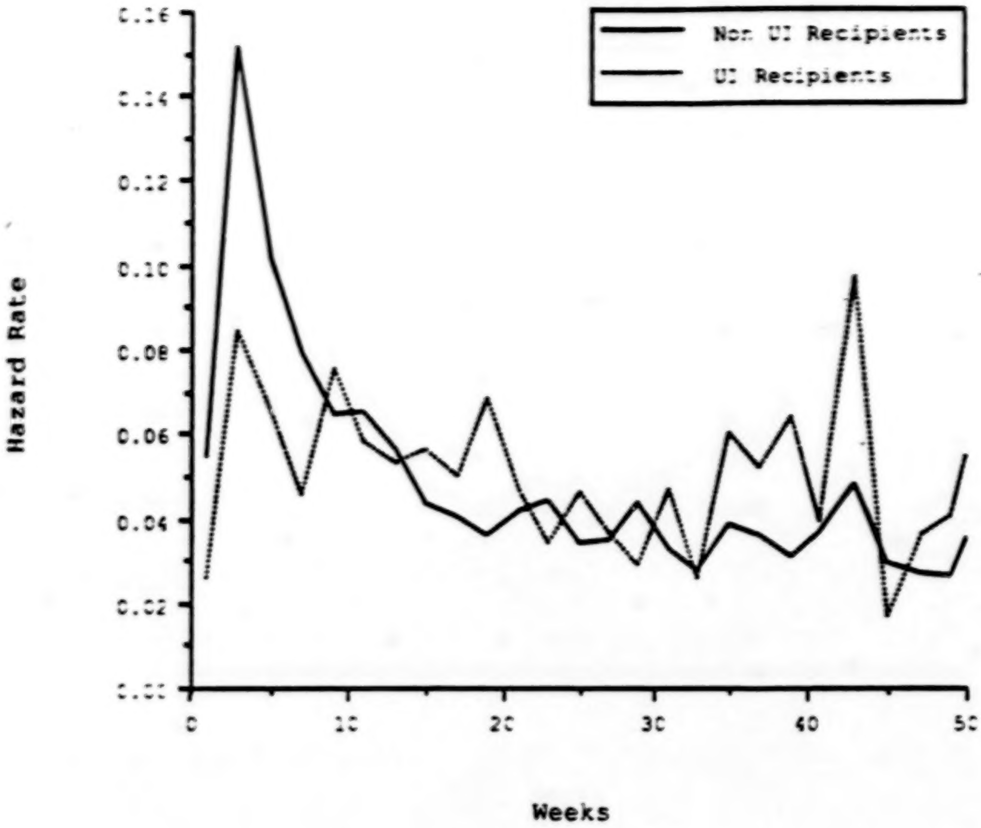
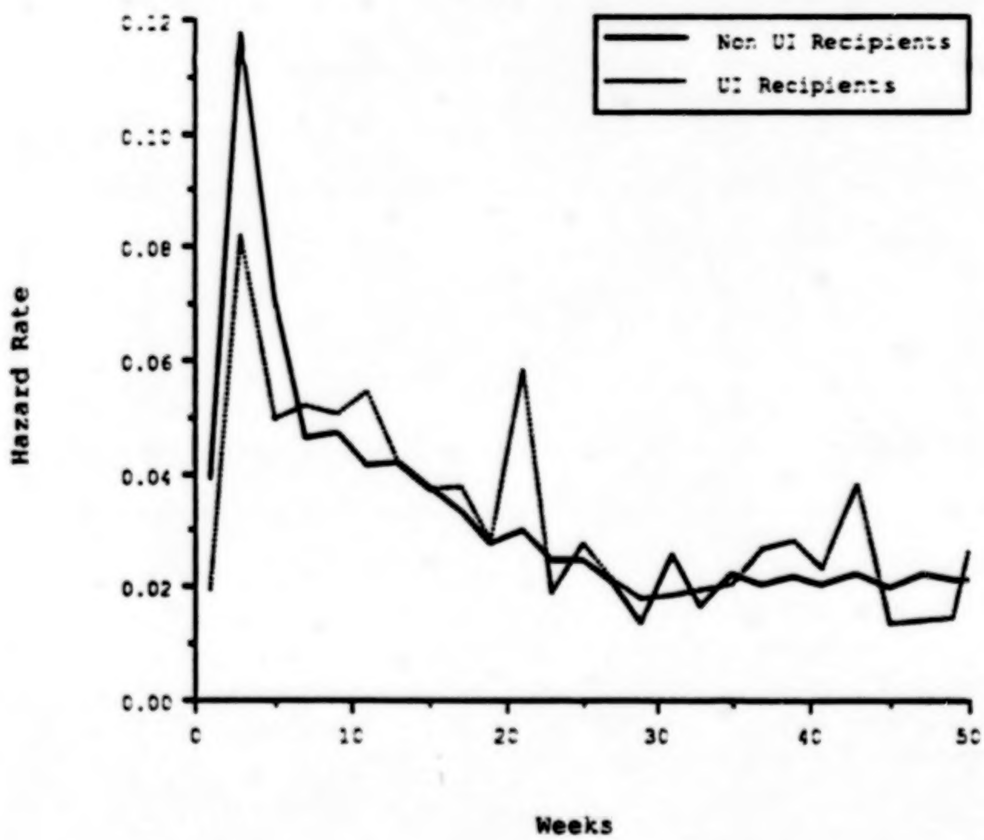


FIGURE 7.1-W
Empirical Hazard Rates for Nonemployment Spells
by UI Status



t, then sharply decreases, and then slowly declines for durations above 10 weeks. Second, there are differences in the form of duration dependence between UI and non-UI episodes. For non-UI episodes, there is a more exaggerated movement in the hazard at low values of t than at the higher values.

At first impression, one might suspect that these findings are in conflict with those obtained in the existing literature. Beginning with the work of Moffitt (1985), several studies have developed a body of evidence to support the contention that an important and complicated interaction effect exists between UI receipt and duration dependence. This evidence applies to data on duration of unemployment, and it shows that the likelihood of leaving unemployment increases near the exhaustion of UI benefits. Unfortunately, there is no simple way of translating these implications for unemployment durations into an analyses of the lengths of nonemployment spells.

To examine whether our data set supports these implications, Figures 7.2–M and 7.2–W present plots of hazard rates for a concept of unemployment duration that more closely matches the measures used in other studies. In particular, these figures interpret "ℓ" in (7.1)–(7.3) as the accumulative number of weeks of UI receipt within single UI-benefit years, which we imputed from our data.[19]

The picture portrayed by these figures is in agreement with the evidence in the literature that hazard rates associated with unemployment durations tend to rise near points at which UI benefits become exhausted (i.e. at 26 and 39 weeks). Especially in the case of men, the plot in Figure 7.2–M reveals the predicted upturns.

7.3 *An Empirical Specification for Spell Lengths in Nonemployment*

These findings indicate that empirical specifications of the probabilities $P(X, t)$ must admit non-montonic duration dependence and allow the form of this dependence to vary according to the attributes X. While the above data analysis explicitly considers only

[19] Our data do not provide information on the number of weeks an individual collected UI during a nonemployment spell, but do indicate the months in which UI collection took place. To impute our measure of ℓ, we assumed that a benefit year began with an individuals' first week of eligibility in the first month of declared receipt. We calculated ℓ as the maximum number of weeks since the start of a benefit year during those months in which UI benefits were collected and an individual was eligible for benefits. The calculation of the hazard rates presented here assumes three-week intervals.

FIGURE 7.2-M
Empirical Hazard Rate for Weeks of UI Receipt
During a Benefit Year

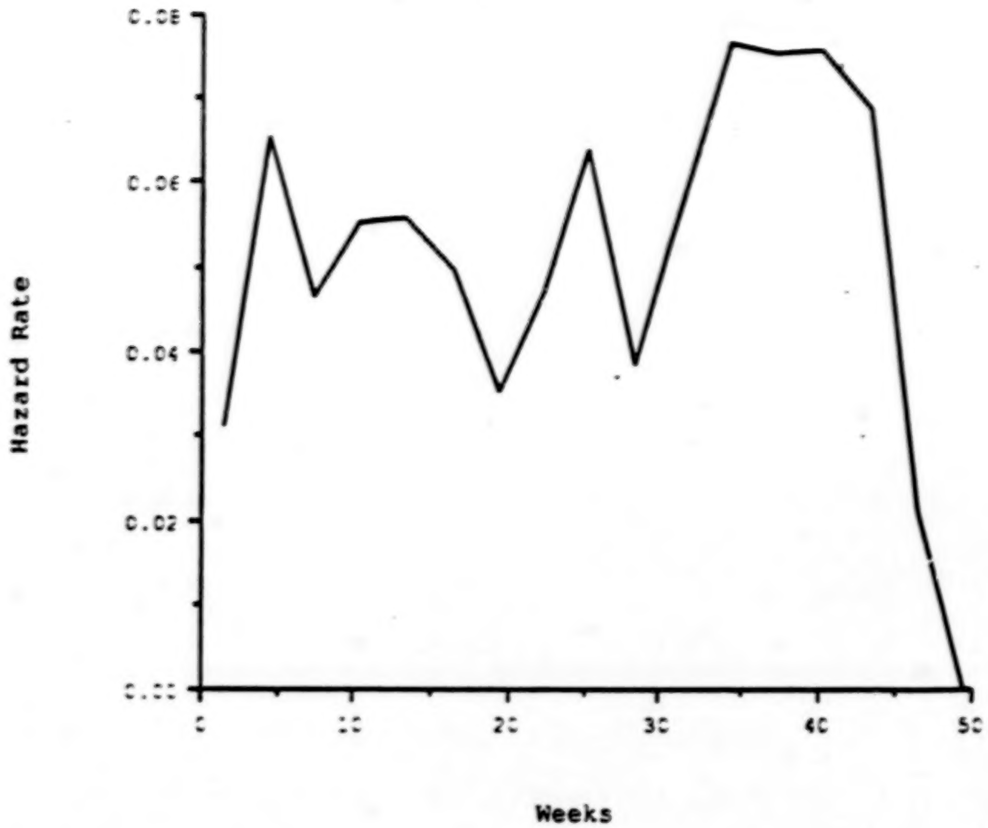
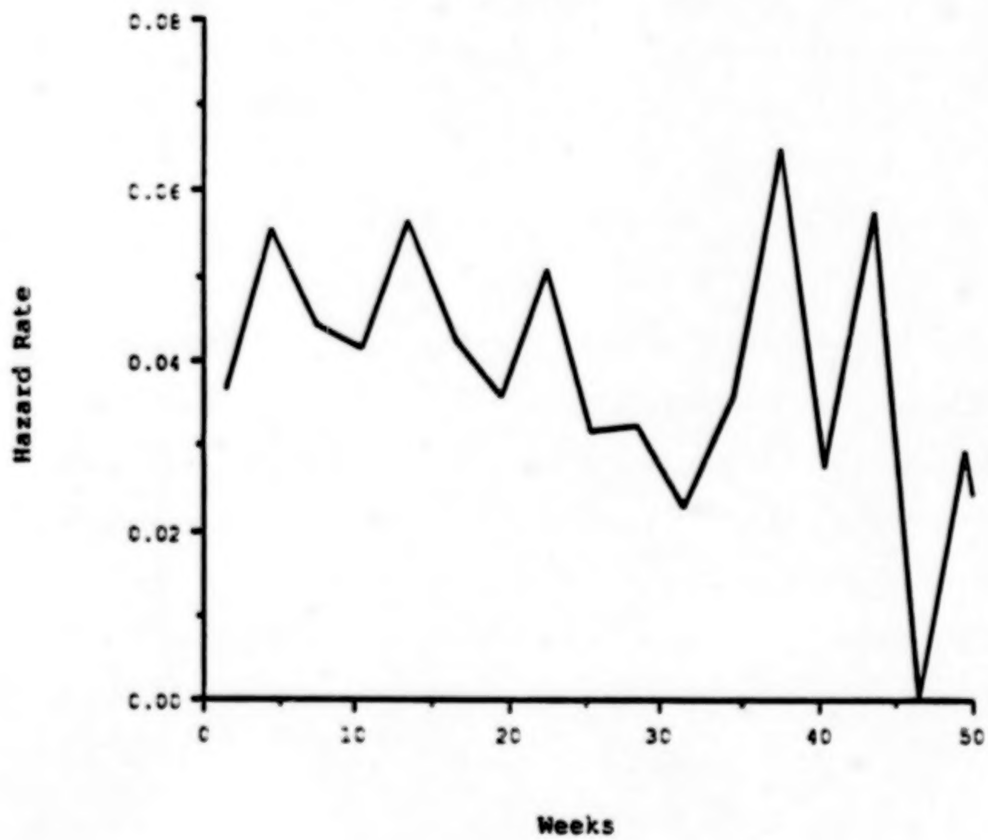


FIGURE 7.2-W
Empirical Hazard Rate for Weeks of UI Receipt
During a Benefit Year



the role of δ as a determinant of duration characteristics, the evidence in the literature and presented in Figures 7.2 clearly suggests that sophisticated interactions are operative between duration and UI entitlements. Accounting for such features rules out "proportional hazards" as a specification for P, which represents one of the most popular choices in the unemployment literature.

The following specification for the probability $P(X,t)$ incorporates the desired features:

$$P(X,t) = \frac{1}{1+e^{X_1\beta+g(t,X_2,\alpha)}} \tag{7.4}$$

where X_1 and X_2 are vectors of variables made up of the covariates X, β is a parameter vector,

$$g(t,X_2,\alpha) = \sum_{j=1}^{K} [\Phi_j(t) - \Phi_{j-1}(t)]\ [\alpha_{0j}X_2 + t\cdot\alpha_{1j}X_2 + t^2\alpha_{2j}X_2] \tag{7.5}$$

with $\Phi_j(t)$ denoting the cumulative distribution function of a normal random variable possessing mean μ_j and variance σ_j^2, and the α_{ij}'s in (7.5) represent parameter vectors. Specification (7.4) models P as a logit function.

The function $g(t,X_2,\alpha)$ determines the duration properties of nonemployment spells. The presence of X_2 in g allows duration dependence to vary according to all the attributes included in X_2. To describe the characteristics of g, suppose X_2 for the moment only consists of an intercept; so $\alpha_{0j}X_2 + t\alpha_{1j}X_2 + t^2\alpha_{2j}X_2 = \alpha_{0j} + \alpha_{1j}t + \alpha_{2j}t^2$. The presence of the *cdf*'s in (7.5) permit one to incorporate spline features in g so that the quadratic polynomial $\alpha_{0j} + \alpha_{1j}t + \alpha_{2j}t^2$ represents g over only a prespecified range of t. In particular suppose one wishes to set $g = \alpha_{01} + \alpha_{11}t + \alpha_{21}t^2$ for values of t between 0 and t^* and to set $g = \alpha_{02} + \alpha_{12}t + \alpha_{22}t^2$ for values of t between t^* and some upper bound $\bar{t}$. To create a specification of g that satisfies the property, assign $K = 2$ in (7.5); fix the three means determining the *cdf*'s as $\mu_0 = 0$, $\mu_1 = t^*$, $\mu_2 = \bar{t}$; and pick very small values for the three standard deviations σ_0, σ_1, and σ_2. These choices for the μ's and the σ's imply that the quantity $\Phi_1(t) - \Phi_0(t) = 1$ over the range $(0,\ t^*)$ and $= 0$ elsewhere, and the quantity $\Phi_2(t) - \Phi_1(t) = 1$ over the range $(t^*,\ \bar{t})$ and $= 0$ elsewhere. Accordingly, g possesses the desired property. Further, $g(t,X_2,\alpha)$ is differentiable in t. With the values of the μ_i and the σ_i set in advance of estimation, $g(t,X_2,\alpha)$ is strictly linear in the parameters α and in

known functions of t and X_2. One can control where each spline or polynomial begins and ends by adjusting the values of the μ's. Also one can control how quickly each spline cuts in and out by adjusting the values of the σ's, with higher values providing for a more gradual and smoother transition from one polynomial to the next.

In the subsequent estimation dealing with nonemployment spells, we pick a specification of $g(t, X_2, \alpha)$ by setting $K = 3$ in (7.5), with $\mu_0 = 0$, $\sigma_0 = 0.5$, $\mu_i = 7$, $\sigma_1 = 0.5$, $\mu_2 = 39$, $\sigma_2 = 2$, μ_3 = above value of highest spell length. Thus, the polynomial $\alpha_{01} + t\alpha_{11}X_2 + t^2\alpha_{21}X_2$ determines g from 0 to about 7 weeks. Over the 6 to 8 week range, g switches to the polynomial $\alpha_{02}+t\alpha_{12}X_2+t^2\alpha_{22}X_2$ which determines its value until about 39 weeks. Over the 35 to the 43 week interval, g again switches to become the polynomial $\alpha_{03}+t\alpha_{13}X_2+t^2\alpha_{23}X_2$ which it remains for the highest values of duration. The empirical analysis estimates the α coefficients.

The following analysis considers several specifications of the explanatory variables incorporated in X_1 and X_2. A full quadratic (i.e. linear, squares and interaction terms) in the demographic characteristics AGE and EDU listed in (6.1) make up X_1, along with the RACE dummy variable. In the case of women, specifications also include the MARRIED and the NUMKIDS variables. Analyses are done separately for men and women, so all of X implicitly accounts for fully interacted gender effects. All the other variables are made a part of X_2 to allow for interactions with duration. The analysis considers two specifications of the UI entitlement variables listed in (6.2), including

$$
(7.6) \qquad \begin{aligned} E_1 &: \textit{WBA} \text{ and } \textit{WE} \text{ ; and} \\ E_2 &: \text{all terms of a full quadratic in } \textit{WBA} \text{ and } \textit{WE}. \end{aligned}
$$

In the construction of X_2, the components of E are fully interacted with the indicator variable δ for UI receipt. The empirical work investigates five specifications of the work-

history variables listed in (6.3) given by

$$
(7.7)\quad
\begin{aligned}
H_1 &: AWE \text{ and } PQ; \\
H_2 &: \text{dummy variables for brackets of } AWE \text{ and } PQ; \\
H_3 &: AWE, HQE, BPE \text{ and } PQ; \\
H_4 &: \text{all terms of a full quadratic in } AWE, HQE \text{ and } BPE \text{ and } PQ; \text{ and} \\
H_5 &: \text{dummy variables indicating brackets for combinations of} \\
&\qquad\qquad AWE, HQE, \text{ and } BPE \text{ and } PQ.
\end{aligned}
$$

Consideration of H_1 provides a basis for comparison with much of the existing literature, and H_2 admits the possibility of nonlinearities in AWE. Specification H_3 expands the set of work-history variables to include other determinants of UI benefits, and H_4 admits simple interactions and nonlinearities in these quantities. Our preferred specification H_5 allows for sophisticated forms of both interactions and nonlinearities in work-history quantities.[20] Finally, X_2 incorporates the macroeconomic variables $UNRATE$ and $EBDUM$ and the UI taxation rate variable $UITAX$ listed in (6.4) and (6.5).

7.4 *Estimation Results*

To estimate the distribution $f(\ell|X)$, we apply conventional maximum likelihood methods of the sort found in duration analysis to compute values for the coefficients β and α appearing in specification (7.4). Our sample consists of observations on nonemployment spell lengths. Our procedure accounts for right censoring when spells are interrupted in progress. We estimate distinct models for men and women.

We explored a wide variety of alternative empirical specifications for the distribution $f(\ell|X)$. To capture differences in duration dependence between UI and non-UI recipients, the following results incorporate the variables δt ,$(1-\delta)t$, δt^2 and $(1-\delta)t^2$ among the interactions $t\,X_2$ and $t^2\,X_2$ appearing in the functions g given by (7.5). After accounting for recipiency status, likelihood ratio tests at conventional levels of significance indicate acceptance of the restriction that no other variables need be incorporated in X_2 in interactions

[20] Specifically, H_5 is made up of dummy variables that indicate the region containing the combination of the three variables AWE, HQE and BPE. In the case of men, H_5 consists of 22 variables; H_5 incorporates 15 variables in the case of women. Appendix B describes the precise formulation of these specifications.

with the polynomial terms t and t^2, including either UI-entitlement or work-history variables.[21] Regarding the inclusion of entitlement variables in X_2 not involved in interactions with the t and t^2 terms, allowing for distinct effects of these variables according to recipiency status means entering the quantities δWBA, δWE, $(1-\delta)WBA$ and $(1-\delta)WE$ as components of X_2. Likelihood ratio tests accept linearity in UI benefit variables favoring specification E_1 over E_2 (defined by (7.6)) when interacted with either δ or $(1-\delta)$. Further, empirical results indicate that UI entitlement variables are not important determinants of nonrecipients' behavior, supporting the elimination of the interactions of UI benefits and the non-UI indicator $(1-\delta)$.[22] Finally, conventional testing procedures indicate the significance of both nonlinearities and mutual interactions in work-history variables,[23] which led us to incorporate the most flexible form of H given by H_5 (involving the set of bracket variables in (7.7)) as components of X_2.

Tables 7.1–M and 7.1–W present coefficient estimates and standard errors for two specifications of the probability $P(X, t)$ consistent with the test results described above: model A and model B. The letters "M" and "W" associated with each table indicate whether the estimates refer to men or women. Model A is a specification that incorporates both of the entitlement variables WBA and WE as factors influencing the nonemployment spell lengths of UI recipients, with separate effects permitted for durations of 1–7, 8–39, and 40+ weeks (i.e. in the different splines). Inspection of the results reveals that the variable δWE enters

[21] Thus, in the specification of g in (7.5), one can accept the hypothesis that $t\alpha_{1j}X_2 + t^2\alpha_{2j}X_2 = (\alpha_{11j}t + \alpha_{12j}t^2)\delta + (\alpha_{21j}t + \alpha_{22j}t^2)(1-\delta)$, where the coefficients α_{11j}, α_{12j}, α_{21j} and α_{22j} are free parameters. We also considered measuring duration as $(t - WE)$ rather than just as t in an attempt to capture the notion of time left until UI exhaustion, but the variables $(t - WE)$ and $(t - WE)^2$ never entered specifications significantly.

[22] While likelihood ratio tests formally reject the hypothesis that the variable $(1-\delta)WBA$ does not enter as a component of X_2 for the 1–7 week spline in the specification reported below, the evidence indicates that this variable becomes insignificant if one allows quit variables to have effects that varies by worker type. Because this more complex specification implies essentially the same predictions as the ones described below based on a simple specification that merely excludes $(1-\delta)WBA$ with only PQ entered as a single component of X_2, we report estimates only for this more straightforward parameterisation.

[23] One cannot, of course, apply likelihood ratio statistics to test among the five specifications of work history variables because these specifications are nonnested. While H_1, H_3 and H_4 are mutually nested, as are H_2 and H_5, these two groups are not nested. Likelihood ratio tests reject H_1 and H_3 in favor of H_4, and reject H_2 in favor of H_5. Our impression is that one would accept H_5 over H_4 using an Akaike information test. We choose H_5 as our base specification to guard against biases in estimates of UI entitlement effects.

TABLE 7.1-M

Parameter Estimates of Nonemployment Duration Probabilities

Estimates of P(X,t)

(Standard Errors in Parentheses)

	Model A			Model B		
Log Likelihood	-12940.985			-12942.573		
Variables in X_1						
AGE	-0.2472 (0.1208)			-0.2559 (0.1206)		
EDU	0.1284 (0.0920)			0.1273 (0.0917)		
AGE*EDU	-0.0011 (0.0045)			-0.0010 (0.0045)		
AGE^2	0.0060 (0.0030)			0.0062 (0.0032)		
EDU^2	-0.0036 (0.0032)			-0.0036 (0.0032)		
RACE	-0.2837 (0.0481)			-0.2829 (0.0486)		
Variables in X_2	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
PQ	0.0351 (0.0568)	-0.2446 (0.0728)	0.0657 (0.1528)	0.0317 (0.0568)	-0.2443 (0.0727)	0.0661 (0.1526)
UITAX	-0.0570 (0.0589)	0.0304 (0.0678)	-0.1007 (0.1817)	-0.0540 (0.0589)	0.0300 (0.0675)	-0.1021 (0.1789)
UNRATE	-0.0025 (0.0112)	-0.0168 (0.0125)	-0.0032 (0.0259)	-0.0023 (0.0112)	-0.0168 (0.0124)	-0.0030 (0.0256)
EBDUM	-0.3448 (0.0611)	-0.3837 (0.0683)	-0.0704 (0.1461)	-0.3480 (0.0610)	-0.3831 (0.0679)	-0.0704 (0.1457)
$(1-\delta)$	-0.7386 (1.3824)	-0.1921 (1.3327)	-1.1449 (1.3416)	-0.6460 (1.3796)	-0.0992 (1.3298)	-1.0521 (1.3367)
$(1-\delta)*t$	0.2699 (0.0757)	-0.0849 (0.0210)	-0.0135 (0.0075)	0.2686 (0.0757)	-0.0849 (0.0210)	-0.0135 (0.0075)
$(1-\delta)*t^2$	-0.0482 (0.0105)	0.0015 (0.0005)	0.00003 (0.00003)	-0.0480 (0.0105)	0.0015 (0.0005)	0.00003 (0.00003)
δ	-1.706 (1.4323)	0.3611 (1.3807)	-1.0309 (1.6911)	-1.3550 (1.4168)	0.4463 (1.3741)	-0.9501 (1.6805)
$\delta*t$	0.5115 (0.1998)	-0.0813 (0.0374)	-0.0017 (0.0242)	0.5074 (0.1997)	-0.0812 (0.0374)	-0.0017 (0.0241)
$\delta*t^2$	-0.0787 (0.0273)	0.0016 (0.0009)	-0.0001 (0.0001)	-0.0785 (0.0273)	0.0016 (0.0009)	-0.0001 (0.0001)
δ*WE	-0.0177 (0.0083)	-0.0215 (0.0068)	0.0011 (0.0182)	-0.0144 (0.0081)	-0.0216 (0.0065)	0.0004 (0.0156)
δ*WBA	0.0033 (0.0019)	-0.0001 (0.0019)	-0.0004 (0.0049)			

TABLE 7.1-W

Parameter Estimates of Nonemployment Duration Probabilities

Estimates of P(X,t)

(Standard Errors in Parentheses)

	Model A			Model B		
Log Likelihood	-14678.397			-14680.740		
Variables in X_1						
AGE	-0.1564 (0.1114)			-0.1556 (0.1115)		
EDU	0.3399 (0.0974)			0.3412 (0.0973)		
AGE*EDU	-0.0159 (0.0048)			-0.0159 (0.0048)		
AGE^2	0.0071 (0.0030)			0.0071 (0.0030)		
EDU^2	0.0041 (0.0029)			0.0041 (0.0029)		
RACE	-0.4115 (0.0532)			-0.4100 (0.0532)		
MARRIED	-0.2840 (0.0408)			-0.2845 (0.0408)		
NUMKIDS	0.0099 (0.0281)			0.0102 (0.0280)		
Variables in X_2	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
PQ	-0.0827 (0.0582)	-0.3606 (0.0632)	-0.1562 (0.0952)	-0.0850 (0.0581)	-0.3584 (0.0632)	-0.1580 (0.0951)
UITAX	-0.1404 (0.0606)	-0.0291 (0.0627)	-0.1409 (0.1127)	-0.1409 (0.0606)	-0.0275 (0.0628)	-0.1416 (0.1125)
UNRATE	0.0271 (0.0126)	0.0048 (0.0126)	-0.0098 (0.0173)	0.0266 (0.0126)	0.0050 (0.0126)	-0.0101 (0.0172)
EBDUM	-0.6565 (0.0663)	-0.5190 (0.0638)	-0.3548 (0.1115)	-0.6581 (0.0663)	-0.5182 (0.0637)	-0.3550 (0.1114)
$(1-\delta)$	-3.3601 (1.3102)	-2.6412 (1.2630)	-3.0886 (1.2636)	-3.3726 (1.3101)	-2.6586 (1.2629)	-3.1010 (1.2636)
$(1-\delta)*t$	0.4553 (0.0786)	-0.0744 (0.0188)	-0.0176 (0.0038)	0.4558 (0.0786)	-0.0745 (0.0188)	-0.0176 (0.0038)
$(1-\delta)*t^2$	-0.0818 (0.0109)	0.0011 (0.0004)	0.00004 (0.00001)	-0.0818 (0.0109)	0.0011 (0.0004)	0.00004 (0.00001)
δ	-3.7805 (1.4408)	-1.4847 (1.3869)	-2.9705 (2.2505)	-3.3931 (1.4289)	-1.7000 (1.3792)	-2.8211 (2.1865)
$\delta*t$	0.5647 (0.2697)	-0.0600 (0.0535)	0.0089 (0.0485)	0.5609 (0.2697)	-0.0604 (0.0533)	0.0089 (0.0479)
$\delta*t^2$	-0.0802 (0.0356)	0.0006 (0.0013)	-0.0002 (0.0003)	-0.0801 (0.0356)	0.0006 (0.0104)	-0.0002 (0.0003)
δ*WE	-0.0284 (0.0117)	-0.0389 (0.0105)	-0.0243 (0.0190)	-0.0266 (0.0115)	-0.0391 (0.0104)	-0.0243 (0.0187)
δ*WBA	0.0050 (0.0030)	-0.0025 (0.0024)	0.0021 (0.0056)			

as significant determinants of spell lengths, but the variable δWBA never enters according to conventional t-tests. Likelihood ratio tests further indicate that weekly benefit amounts are insignificant factors when one entertains their joint elimination from all splines.[24] In recognition of these findings, the estimation reported for model B excludes WBA as a determinant of nonemployment durations.

7.5 *Implications of the Empirical Findings*

These empirical results support the contention that the benefits offered by UI programs influence the amount of time that youths spend between jobs. While the weekly benefit amounts paid by programs have essentially no effect on the durations of nonemployment spells, the number of weeks of UI eligibility offered by a program does have a significant impact on spell lengths. Referring to the estimates associated with model B, for UI recipients an increase in WE raises the probability of remaining in nonemployment (i.e. the probability $P(X, t)$) during the first 1–39 weeks of a spell experienced by men and has basically no effect on this probability after 39 weeks. (This implication follows from the observation that δWE has a negative coefficient in the splines 1–7 and 8–39 weeks and has a positive but insignificant coefficient in the 40+ week spline.) In the case of women UI recipients, an increase in WE raises the probability of staying in nonemployment throughout the entire length of a spell.

To explore the policy implications of these findings, Figures 7.3–M, 7.3–W, 7.4–M, 7.4–W and 7.5–M present plots of estimated survivor functions for nonemployment spells for several configurations of the covariates X. Associated with each figure title is a letter "M" or "W": the letter "M" denotes that the plots are for white men; and "W" signifies graphs for white women who are unmarried without children.[25] All figures present survivor plots associated with 25-year-old high-school graduates. The predictions rely on model B estimates in recognition of the evidence that weekly benefit amounts do not affect nonemployment durations.[26]

[24] According to our evidence, the finding that WBA is a statistically insignificant determinant of $f(\ell|X)$ does not change when one substitutes a measure of the wage replacement ratio for WBA. Wage replacement ratios, regardless of how they are measured, are also statistically insignificant at conventional levels of confidence.

[25] Further, it is assumed that an individual did not quit his or her job (so $PQ = 0$) and $EBDUM = 0$. The variables $UNRATE$ and $UITAX$ are set at their sample means which are 8% and 1.5% respectively.

[26] The predictions presented below do not change if one instead uses the estimates obtained for model A.

FIGURE 7.3-M
Survivor Functions for Work History H_1 Under
Various UI Regimes

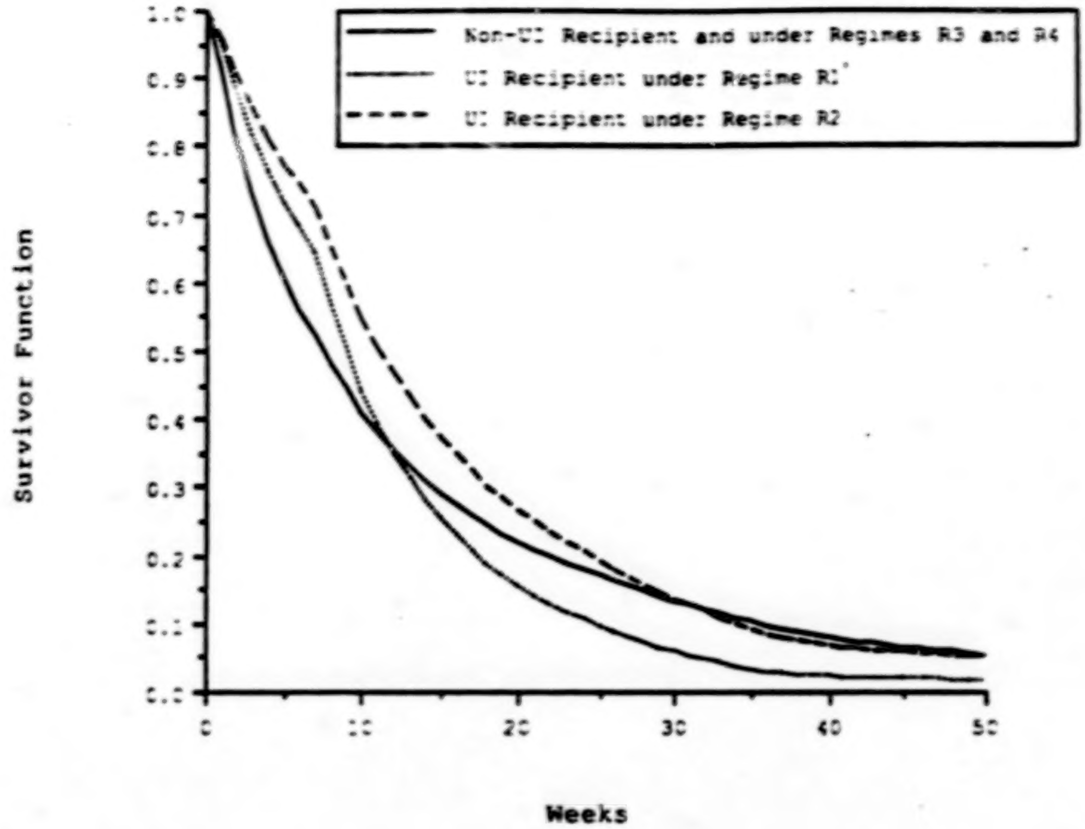


FIGURE 7.3-W
Survivor Functions for Work History H_1 Under
Various UI Regimes

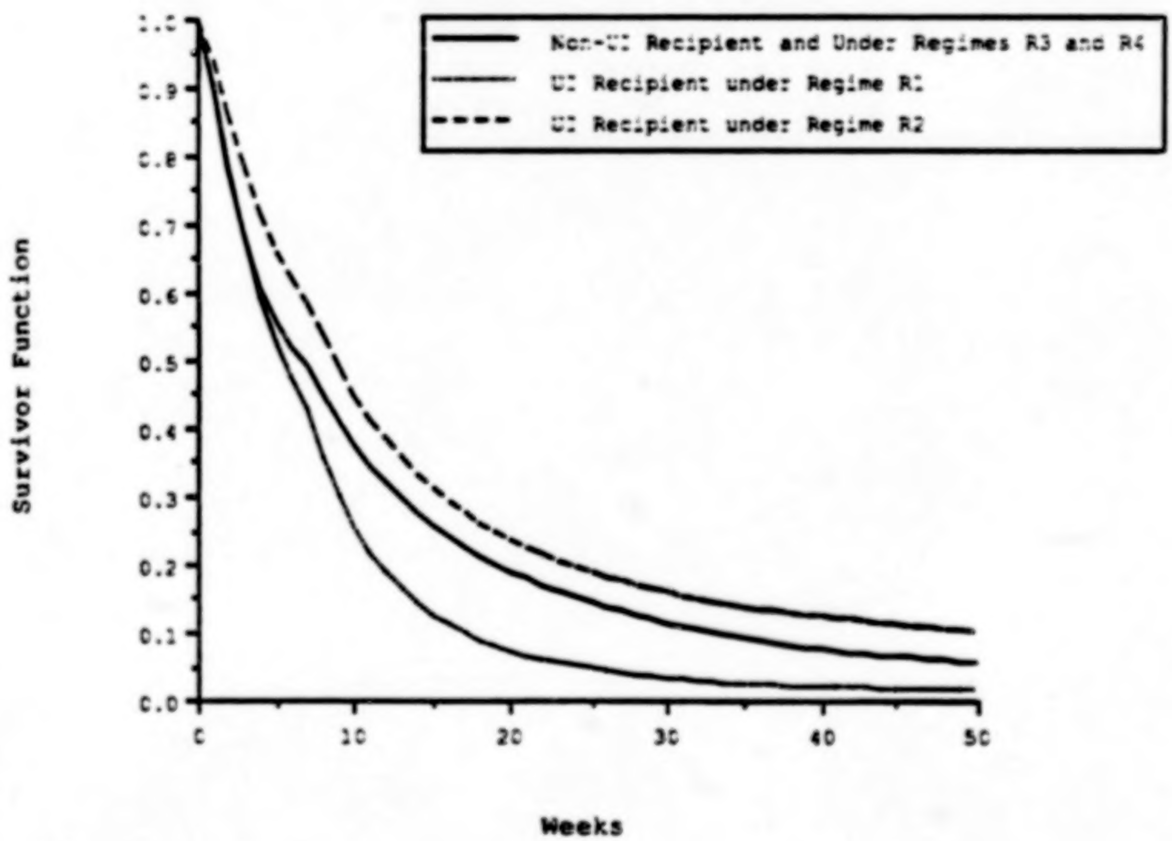


FIGURE 7.4-M
Survivor Functions for Work History H_m Under Various UI Regimes

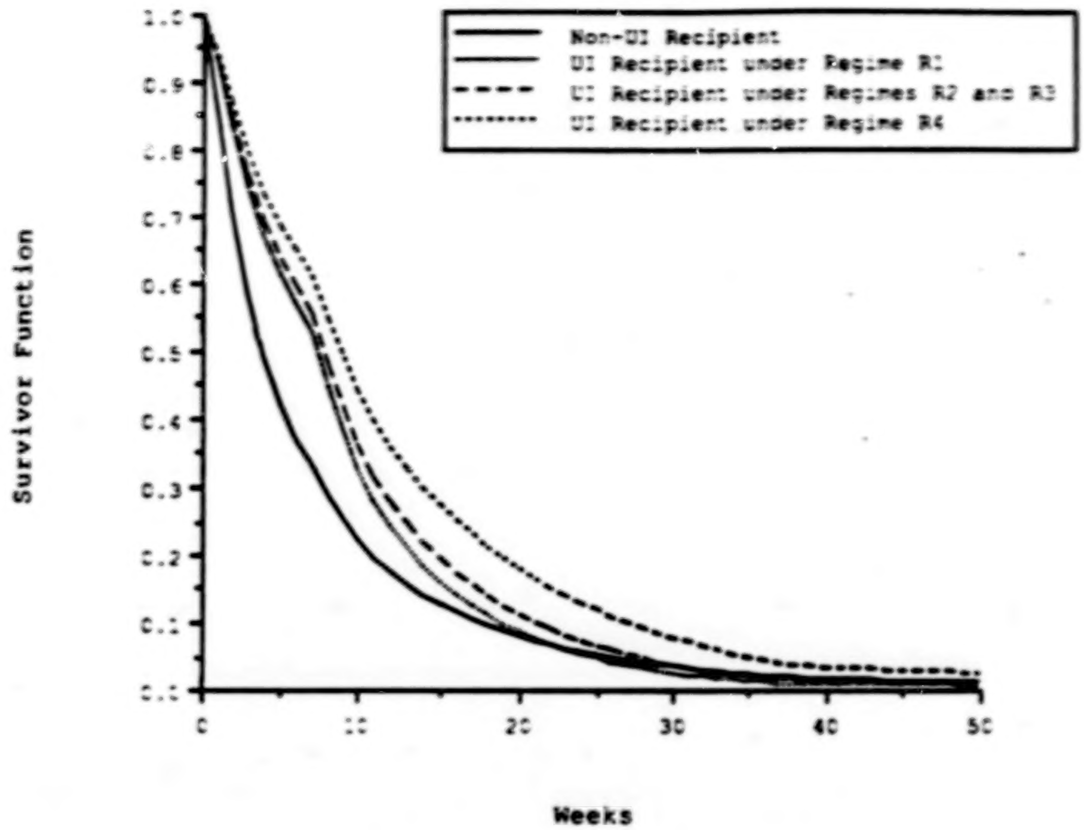


FIGURE 7.4-W
Survivor Functions for Work History H_m Under Various UI Regimes

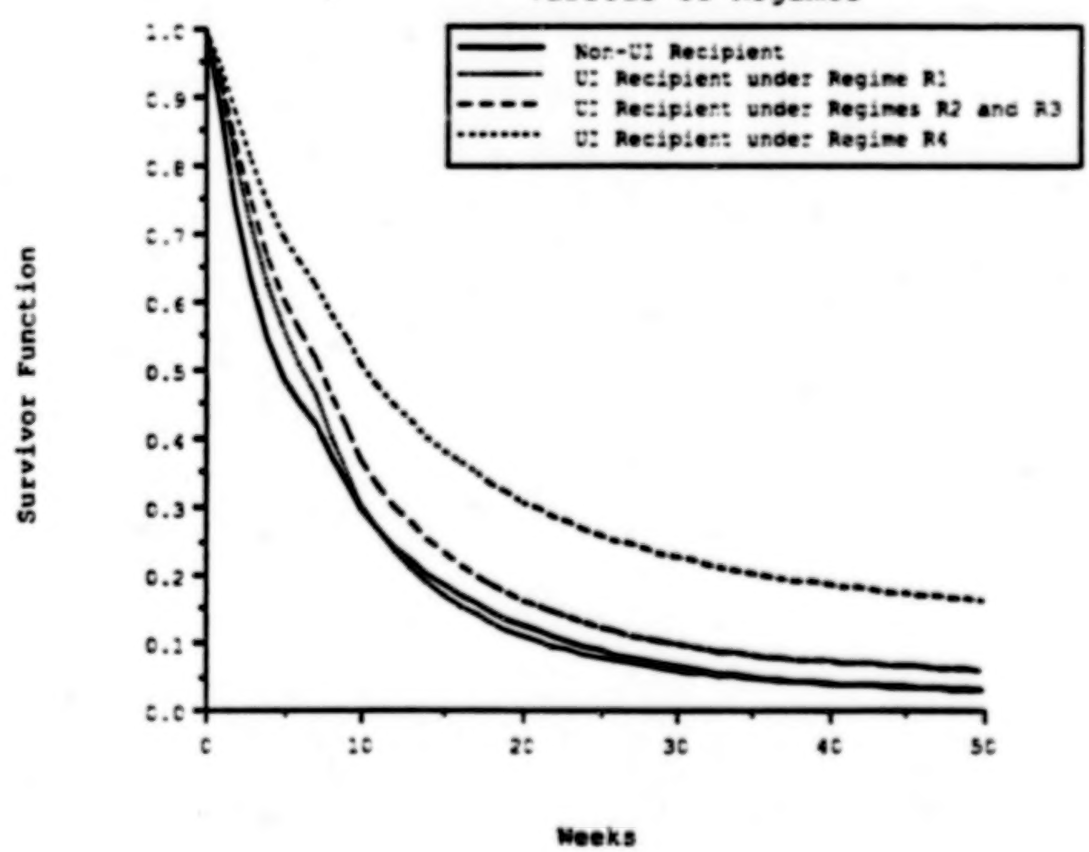
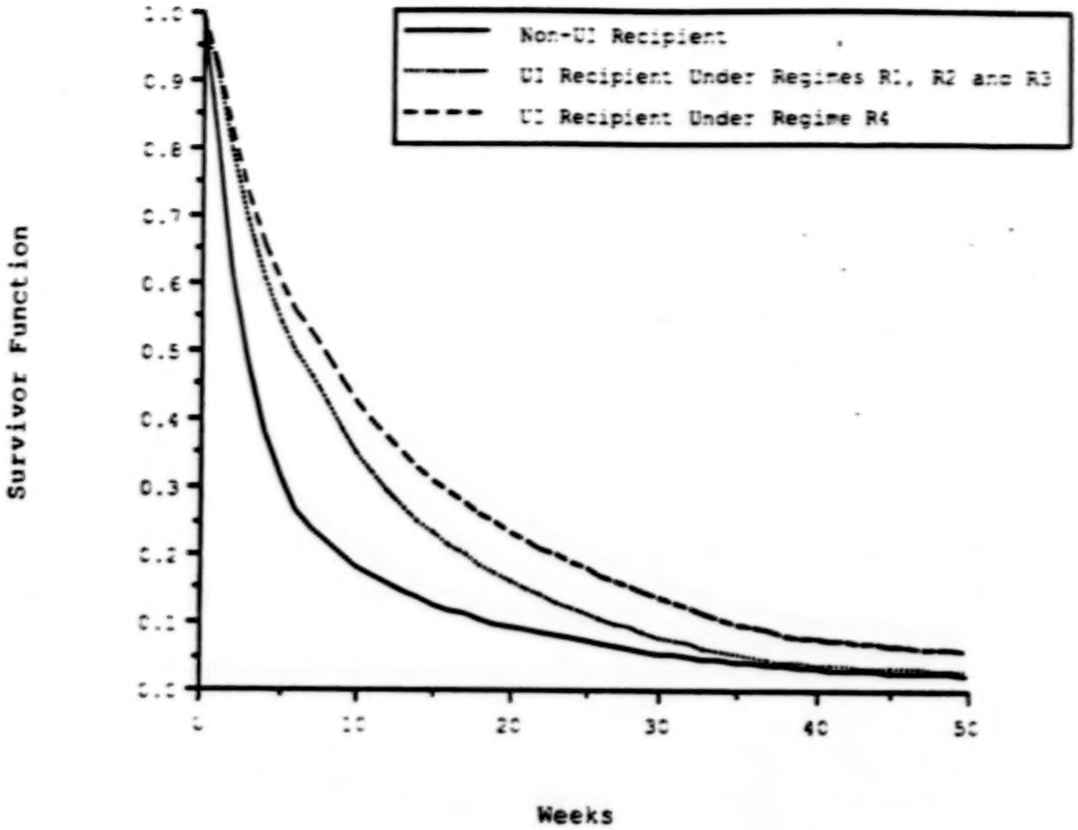


FIGURE 7.5-M
Survivor Functions for Work History H_h Under
Various UI Regimes



These figures characterize survivor functions for the three representative worker types operating under the four prototype UI policy regimes described in Section 6.3 (see descriptions (6.6), (6.7) and (6.8)). Figures 7.3 portray the situation for a low-intensity worker (i.e. H_ℓ) under regimes R_3 and R_4 in which this individual is noneligible and a non-UI recipient during the nonemployment spell, and under regimes R_1 and R_2 as a UI recipient. Figures 7.4 characterize analoguous situations for a medium-intensity worker (i.e. H_m) as a non-UI recipient and as a recipient under regimes R_1, R_2, R_3 and R_4. As indicated in (6.8), the value of WE assigned to worker type H_m is the same under R_2 and R_3; so a single curve accounts for the effects of these regimes. Finally, Figure 7.5–M describes the circumstances for a high-intensity worker (i.e. H_h). For this worker type, WE is the same under R_1, R_2 and R_3, and a single plot summarizes their effect. A women's version of Figure 7.5–M is not presented because worker type H_h is quite atypical for women, as Table 6.2–W reveals.

Inspection of these figures suggests three conclusions. First, in the case of men, UI recipients experience longer nonemployment spells on average than non-UI recipients with the same attributes, at least up to the point where weeks of UI eligibility run out. Second, in the case of women, there is no systematic ranking of nonemployment durations between individuals collecting UI and those not receiving benefits. Third, regardless of whether one considers men or women, UI-recipients with more weeks of UI eligibility (i.e. higher WE) tend to experience longer spells.

Shifts in the *WBA* still have an imperceptable effect on nonemployment durations.

8. The Effects of UI on Unemployment Proportions

This section presents estimated variants of the distribution describing the proportion of a nonemployment spell categorized as unemployment. The previous discussion designates this time-proportion distribution as $f(\rho|\ell, \delta, E, T, PA)$, which one may simply write as $f(\rho|\ell, X)$ where the covariates X incorporate all the variables making up the measures δ, E, H, Z, M, and T. The estimation results obtained here provide an indication of the role that a youth's UI entitlements play in explaining his or her decision to report nonworking time as unemployment or as OLF.

8.1 *Specifying a Time-Proportion Distribution*

To admit a flexible form for $f(\rho \mid \ell, X)$, this analysis develops a statistical framework that predicts whether ρ falls within particular brackets. Divide the sample space of ρ into the three regions: $I_n = \{\rho : \rho = 0\}$; $I_s = \{\rho : 0 < \rho < 1\}$; and $I_a = \{\rho : \rho = 1\}$. The bracket I_n designates a situation in which no unemployment occurs during a nonemployment episode; the interval I_s signifies the reporting of some unemployment; and I_a denotes the circumstance in which an individual classifies all of a spell as unemployment. To refine the category of some unemployment, further divide the interval I_s into the following seven sub-brackets: $I_{s_1} = \{\rho : 0 < \rho \leq .15\}$; $I_{s_2} = \{\rho : .15 < \rho \leq .30\}$; $I_{s_3} = \{\rho : .30 < \rho \leq .45\}$; $I_{s_4} = \{\rho : .45 < \rho < .55\}$; $I_{s_5} = \{\rho : .55 \leq \rho < .70\}$; $I_{s_6} = \{\rho : .70 \leq \rho < .85\}$; and $I_{s_7} = \{\rho : .85 \leq \rho < 1\}$. Define the probabilities:

$$(8.1) \qquad Pr_i(\ell, X) = \text{Prob}(\rho \,\epsilon\, I_i \mid \ell, X) \qquad i = n, s, a, s_1, \ldots, s_7.$$

These quantities determine the likelihood that the value of ρ falls in the range covered by the interval I_i for a nonemployment spell characterized by attributes X that lasts ℓ weeks. Of course, $Pr_s(\ell, X) = \sum_{j=s_1}^{s_7} Pr_j(\ell, X)$.

The statistical model introduced to parameterize these probabilities is a member of the multinomial logit class. In particular, the specifications estimated in the subsequent analysis take the form:

$$(8.2) \qquad Pr_i(\ell, X) = \frac{e^{X_1\beta_i + g(\ell, X_2, \alpha_i)}}{\sum_{j=n,s,a} e^{X_1\beta_j + g(\ell, X_2, \alpha_j)}}, \qquad i = n, s, a,$$

and

$$(8.3) \qquad Pr_k(\ell, X)/Pr_s(\ell, X) = \frac{e^{X_1\beta_k + g(\ell, X_2, \alpha_k)}}{\sum_{j=s_1}^{s_7} e^{X_1\beta_j + g(\ell, X_2, \alpha_j)}} \qquad k = s_1, \ldots s_7,$$

where all quantities are defined analogously to those appearing in (7.4). Since

$$Pr_{s_k}(\ell, X)/Pr_s(\ell, X) = \mathrm{Prob}\,(\rho \in I_{s_k} \mid \rho \in I_s, \ell, X),$$

the quantities in (8.3) represent the probabilities that ρ falls in the sub-brackets I_{s_k} conditional on ρ being between 0 and 1. Thus, parameterization (8.2) models the events $\rho \in I_n$, $\rho \in I_s$ and $\rho \in I_a$ as a three-state multinomial logit, and parameterization (8.3) models the events $\rho \in I_{s_k}$ conditional on $\rho \in I_s$ as a seven-state multinomial logit. The functions $g(\ell, X_2, \alpha)$ appearing in these specifications capture how cell probabilities vary in response to changes in the lengths of nonemployment spells, instead of determining any sort of duration dependence which was their role in the previous discussion. The $g(\cdot)$ functions in (8.2) are specified in the same way as designated in Section 7.3, with splines turning on and off at 0, 7 and 39 weeks. The functions $g(\cdot)$ appearing in (8.3) have the same form for the splines 7–39 and 40+ weeks, but the splines covering the range 1–7 require modifications which are described below to account for the fact that ρ falls in some brackets with zero probability for each value of $\ell \leq 7$.

8.2 *Estimation Results for the Broad Classification of Unemployment Proportions*

Even a casual inspection of the findings reported in Tables 6.1–M and 6.1–W indicates that one captures most of the variation in the values of ρ across nonemployment spells in the YNLS by analyzing movement among the three categories: $\rho = 0$; $0 < \rho < 1$; and $\rho = 1$. For men, only about 20–25 percent of the spells involve time allocated to both unemployment and OLF during the spell (i.e. involve the situation $0 < \rho < 1$), regardless of whether one considers just UI recipients or not. For women, this figure rises to around 40 percent. Summarizing the movement of ρ among these broad classifications requires measurement of the three probabilities: $Pr_n \equiv Pr_n(\ell, X)$ = the likelihood of $\rho = 0$ or of no unemployment during a nonemployment spell; $Pr_s \equiv Pr_s(\ell, X)$ = the likelihood of $0 < \rho < 1$ or of some unemployment; and $Pr_a \equiv Pr_a(\ell, X)$ = the likelihood of $\rho = 1$ or of all unemployment.

To estimate these probabilities, we apply standard maximum likelihood procedures in a multinomial logit framework to compute values for the parameters β and α appearing in specification (8.2). Our sample consists of observations on the fractions of each nonemployment spell reported as unemployment. The values of the covariates X are set at the time of entry into the nonemployment spell associated with the observation. We estimate separate models for men and women.

The covariates X_1 and X_2 incorporated in specifications (8.2) of the probabilities Pr_n, Pr_s and Pr_a are made up of the same variables introduced in Sections 7.3 and 7.4. In particular, X_1 includes demographic characteristics. The set of interactions ℓX_2 and $\ell^2 X_2$ appearing in the functions $g(\cdot)$ – specified by (7.5) with ℓ replacing t – contain the terms $\delta\ell$, $(1-\delta)\ell$, $\delta\ell^2$ and $(1-\delta)\ell^2$, which allows for differences in the relationships linking nonemployment spell lengths and probabilities according to recipiency status.[27] Concerning the components of X_2 not involved in interactions with the ℓ and the ℓ^2 terms, the analysis incorporates the macroeconomic and the UI-tax-structure variables along with the flexible set of work-history variables designated by H_5 in (7.7).[28] In addition, the analysis includes the variables $\delta\, WBA$ and $\delta\, WE$ as components of X_2 to capture the effects of UI benefits on the fraction of a nonemployment spell reported as unemployment by UI recipients.[29] Likelihood ratio tests accept linearity in entitlement variables when interacted with δ. Further, test results support the elimination of the variables $(1-\delta)\, WBA$ and $(1-\delta)\, WE$ at conventional levels of confidence, which indicates that UI entitlements are not significant determinants of nonrecipients' behavior.

[27] It is crucial to recognise that no variables of the form δX_2 (i.e. interactions of variables with δ) enter the specification of the "no employment" probability Pr_n. If UI receipt is always accompanied by part of a nonemployment spell being reported as unemployment – which of course, should be the case – then an indication of UI receipt means that $Pr_n = \text{Prob}(\rho = 0 \mid \ell, X) = 0$. Formally, this implies that the β coefficient associated with the indicator variable in Pr_n takes a value of minus infinity. We set this coefficient to account for this fact. Also, this factor motivated us to normalise parameters associated with the probability corresponding to the event $\rho = 1$ rather than to the event $\rho = 0$. In the subsequent analysis, variables of the form δX_2 enter specifications of both of the other probabilities Pr_s and Pr_a.

[28] Likelihood ratio and Akaike Information test results indicate that the simpler specifications of the work-history variables given by H_1, H_2, H_3 and H_4 are rejected in favor of the more elaborate formulation H_5 as determinants of the probabilities Pr_n, Pr_s and Pr_a.

[29] For reasons described in footnote 27, these variables enter as determinants of the probabilities Pr_s and Pr_a, but $\delta\, WBA$ and $\delta\, WE$ are not entered in the specification of Pr_n.

Tables 8.1–M and 8.1–W present parameter estimates associated with the time proportion probabilities given by (8.2). As before, the designation "M" in a table heading identifies results for men and "W" denotes values for women. The first page of each table reports estimates corresponding to the "some unemployment" probability Pr_s, and the second page gives results for the "no unemployment" probability Pr_n (in which $\delta\, WBA$ and $\delta\, WE$ do not appear since $Pr_n = 0$ for UI recipients). As an arbitrary normalization, the coefficients in the "all unemployment" probability are set equal to zero; so Pr_s and Pr_n are measured relative to Pr_a. Two sets of estimates appear in each table: model A and model B. Model A is a parameterization that includes both of the UI benefit variables WBA and WE as determinants of the amount of unemployment experienced by UI recipients during nonemployment episodes. The analysis constrains coefficient estimates associated with these variables to be equal across the spell lengths of 1–7 and 8–39 weeks because only a small number of UI recipients have nonemployment spells less than 8 weeks.[30] Inspection of the findings for men reveals that the variable $\delta\, WBA$ enters as a significant determinant of the classification of ρ, but the variable $\delta\, WE$ never enters individually in any spline according to conventional t-tests or jointly in all splines according to a likelihood ratio test. For women, neither $\delta\, WBA$ or $\delta\, WE$ enters as a significant determinant of the likelihood that ρ falls in various regions, regardless of whether one applies individual or joint testing procedures. In recognition of these findings, model B reports parameter estimates with $\delta\, WE$ excluded in the case of men, and with both $\delta\, WBA$ and $\delta\, WE$ eliminated in the case of women.

Inspection of the results for model B reveals either small or nonexistent effects of UI entitlements on the likelihood that individuals shift their classification of nonemployment from partial to full unemployment given their recipiency status. According to the findings in Table 8.1–M, for men an increase in the weekly benefit amount reduces the probability Pr_s relative to Pr_a for nonemployment spell lengths in the range of 1–39 weeks – this is the meaning of the negative coefficient estimate on the variable $\delta\, WBA$ associated with this range

[30] In the case of men, only 34 UI recipients have spells 7 weeks or less. The number is 22 in the case of women. While we constrained the effects of the entitlement variables WBA and WE to be equal for recipients in the 1–39 week range, we allowed the polynomials in ℓ to vary freely with only the quadratic term in the 1-7 week splines eliminated.

TABLE 8.1-M

Parameter Estimates of Time Proportion Probabilities of Some, No, and All Unemployment

Estimates of Pr_s

(Standard Errors in Parentheses)

	Model A			Model B		
Log Likelihood	-3170.917			-3172.063		
Variables in X_1						
AGE	-0.2131 (0.3277)			-0.1890 (0.3277)		
EDU	-0.2441 (0.2448)			-0.2682 (0.2448)		
AGE*EDU	-0.0010 (0.0115)			-0.0005 (0.0115)		
Age^2	0.0037 (0.0079)			0.0037 (0.0079)		
EDU^2	0.0147 (0.0084)			0.0154 (0.0084)		
RACE	0.1077 (0.1169)			0.1152 (0.1167)		
Variables in X_2	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
PQ	0.5197 (0.2297)	0.0593 (0.1652)	-0.3030 (0.3467)	0.5244 (0.2296)	0.0620 (0.1653)	-0.3000 (0.3466)
UITAX	-0.0312 (0.2124)	-0.0035 (0.1538)	0.7088 (0.3687)	-0.0173 (0.2117)	0.0008 (0.1541)	0.7096 (0.3684)
UNRATE	-0.0569 (0.0427)	-0.0730 (0.0286)	-0.0551 (0.0566)	-0.0582 (0.0424)	-0.0698 (0.0285)	-0.0547 (0.0566)
EBDUM	-0.0983 (0.2321)	0.0190 (0.1561)	-0.7023 (0.3325)	-0.1028 (0.2320)	0.0373 (0.1556)	-0.6888 (0.3291)
$(1-\delta)$	-1.2605 (3.9029)	3.3234 (3.7218)	2.1887 (3.8612)	-1.3717 (3.9042)	3.1659 (3.7237)	2.0666 (3.8606)
$(1-\delta)*l$	1.7880 (0.4380)	0.0313 (0.0464)	0.0413 (0.0138)	1.7839 (0.4379)	0.0316 (0.0464)	0.0412 (0.0138)
$(1-\delta)*l^2$	-0.1591 (0.0515)	0.0002 (0.0011)	-0.0001 (0.00005)	-0.1586 (0.0515)	0.0002 (0.0011)	-0.0001 (0.00005)
δ	3.2388 (3.8770)	3.7037 (3.8488)	-3.5758 (4.1701)	3.6329 (3.8649)	4.1388 (3.8376)	-3.5218 (4.1532)
$\delta*l$	-0.0097 (0.1316)	-0.1309 (0.0891)	0.1241 (0.0407)	-0.0012 (0.1305)	-0.1307 (0.0889)	0.1235 (0.0405)
$\delta*l^2$		0.0042 (0.0020)	-0.0004 (0.0001)		0.0042 (0.0020)	-0.0004 (0.0001)
δ*WBA	-0.0071 (0.0033)		0.0044 (0.0098)	-0.0076 (0.0032)		0.0054 (0.0084)
δ*WE	0.0177 (0.0139)		0.0071 (0.0340)			

TABLE 8.1-M (cont.)

Parameter Estimates of Time Proportion Probabilities of Some, No, and All Unemployment

Estimates of Pr_r

(Standard Errors in Parentheses)

	Model A			Model B		
Log Likelihood	-3170.917			-3172.063		
Variables in X_r						
AGE	0.1902 (0.2924)			0.1946 (0.2926)		
EDU	-0.1603 (0.2424)			-0.1723 (0.2427)		
AGE*EDU	-0.0036 (0.0111)			-0.0038 (0.0111)		
AGE^2	-0.0049 (0.0073)			-0.0050 (0.0073)		
EDU^2	0.0165 (0.0078)			0.0168 (0.0076)		
RACE	-0.3695 (0.1163)			-0.3673 (0.1163)		
Variables in X_r	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
PQ	1.9100 (0.1231)	1.3348 (0.1774)	0.8829 (0.4601)	1.9103 (0.1231)	1.3359 (0.1774)	0.8858 (0.4600)
UITAX	-0.1281 (0.1381)	0.1722 (0.1911)	0.0196 (0.5940)	-0.1248 (0.1381)	0.1749 (0.1912)	0.0190 (0.5937)
UNRATE	-0.0531 (0.0264)	-0.1575 (0.0365)	-0.0083 (0.0820)	-0.0534 (0.0264)	-0.1561 (0.0365)	-0.0081 (0.0820)
EBDUM	0.1491 (0.1478)	0.3435 (0.1966)	-1.2794 (0.4579)	0.1477 (0.1478)	0.3520 (0.1965)	-1.2691 (0.4566)
$(1-\delta)$	-1.6657 (3.4422)	-0.8163 (3.3353)	-3.6433 (3.3596)	-1.6440 (3,4471)	-0.8144 (3.3402)	-3.6302 (3.5988)
$(1-\delta)*l$	0.4593 (0.1664)	-0.0515 (0.0517)	0.0413 (0.0253)	0.4585 (0.1664)	-0.0517 (0.0517)	0.0413 (0.0253)
$(1-\delta)*l^2$	-0.0729 (0.0234)	0.0013 (0.0013)	-0.0001 (0.0001)	-0.0728 (0.0234)	0.0013 (0.0013)	-0.0001 (0.0001)

TABLE 8.1-W

Parameter Estimates of Time Proportion Probabilities of Some, No, and All Unemployment

Estimates of Pr_s

(Standard Errors in Parentheses)

	Model A			Model B		
Log Likelihood	-3337.304			-3338.234		
Variables in X_1						
AGE	-0.1275 (0.3329)			-0.1286 (0.3325)		
EDU	-0.2303 (0.2931)			-0.2314 (0.2928)		
AGE*EDU	0.0162 (0.0138)			0.0164 (0.0138)		
AGE^2	-0.0036 (0.0087)			-0.0036 (0.0087)		
EDU^2	-0.0024 (0.0062)			-0.0027 (0.0061)		
RACE	-0.1848 (0.1439)			-0.1747 (0.1430)		
MARRIED	0.1765 (0.1158)			0.1717 (0.1186)		
NUMKIDS	0.2004 (0.0854)			0.2025 (0.0853)		
Variables in X_2	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
PQ	0.7971 (0.2144)	0.3457 (0.1770)	0.2909 (0.4479)	0.7923 (0.2136)	0.3439 (0.1770)	0.2641 (0.4454)
UITAX	-0.0134 (0.2290)	-0.2193 (0.1701)	0.4934 (0.4315)	-0.0082 (0.2275)	-0.2122 (0.1700)	0.5068 (0.4250)
UNRATE	-0.0367 (0.0473)	-0.1349 (0.0342)	-0.0737 (0.0733)	-0.0363 (0.0472)	-0.1339 (0.0339)	-0.0624 (0.0716)
EBDUM	-0.2524 (0.2588)	-0.0478 (0.1738)	-0.2343 (0.3822)	-0.2518 (0.2580)	-0.0437 (0.1731)	-0.2394 (0.3706)
$(1-\delta)$	-2.1372 (4.0388)	3.1426 (3.8889)	3.2672 (4.5213)	-2.1290 (4.0372)	3.1351 (3.8878)	3.3437 (4.5142)
$(1-\delta)*l$	1.8732 (0.4227)	0.1793 (0.0535)	0.0444 (0.0631)	1.8723 (0.4228)	0.1790 (0.0535)	0.0447 (0.0628)
$(1-\delta)*l^2$	-0.1637 (0.0500)	-0.0031 (0.0013)	-0.0001 (0.0004)	-0.1635 (0.0500)	-0.0031 (0.0013)	-0.0001 (0.0004)
δ	1.3425 (4.0091)	1.8005 (4.0577)	4.6489 (5.2444)	1.8422 (3.9741)	2.2195 (4.0412)	3.5046 (5.1781)
$\delta*l$	0.0178 (0.1674)	0.1295 (0.1124)	0.0195 (0.1093)	0.0088 (0.1667)	0.1295 (0.1105)	0.0133 (0.0951)
$\delta*l^2$		-0.0013 (0.0027)	0.00002 (0.0007)		-0.0013 (0.0027)	0.00004 (0.0006)
δ*WE	0.0063 (0.0179)		-0.0043 (0.0077)			
δ*WPA	0.0030 (0.0045)		-0.0329 (0.0365)			

TABLE 8.1-W (cont.)

Parameter Estimates of Time Proportion Probabilities of Some, No, and All Unemployment

Estimates of Pr_n

(Standard Errors in Parentheses)

	Model A			Model B		
Log Likelihood	-3337.304			-3338.234		
Variables in X_1						
AGE	-0.2287 (0.3072)			-0.2289 (0.3072)		
EDU	-0.0088 (0.2717)			-0.0102 (0.2717)		
AGE*EDU	0.0024 (0.0115)			0.0026 (0.0115)		
AGE^2	0.0041 (0.0078)			0.0040 (0.0078)		
EDU	0.0028 (0.0057)			0.0027 (0.0057)		
RACE	-0.4889 (0.1336)			-0.4827 (0.1335)		
MARRIED	0.7722 (0.1097)			0.7688 (0.1096)		
NUMKIDS	0.2701 (0.0787)			0.2717 (0.0787)		
Variables in X_2	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks	Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
PQ	1.9740 (0.1323)	1.2354 (0.1770)	1.0988 (0.4637)	1.9723 (0.1323)	1.2343 (0.1770)	1.0920 (0.4614)
UITAX	0.0581 (0.1461)	-0.0014 (0.1799)	0.4595 (0.4568)	0.0598 (0.1460)	0.0038 (0.1798)	0.4718 (0.4517)
UNRATE	-0.0362 (0.0298)	-0.1289 (0.0371)	-0.0436 (0.0761)	-0.0361 (0.0298)	-0.1283 (0.0370)	-0.0518 (0.0747)
EBDUM	-0.0487 (0.1659)	-0.1866 (0.1898)	-0.3381 (0.4098)	-0.0484 (0.1659)	-0.1839 (0.1895)	-0.3431 (0.4005)
$(1-\delta)$	1.5836 (3.7781)	1.4514 (3.6243)	0.4410 (4.3204)	1.5923 (3.7786)	1.4449 (3.6246)	0.5082 (4.3104)
$(1-\delta)*l$	0.2432 (0.1832)	0.1509 (0.0541)	0.0461 (0.0632)	0.2421 (0.1832)	0.1506 (0.0541)	0.0465 (0.0629)
$(1-\delta)*l^2$	-0.0368 (0.0257)	-0.0027 (0.0013)	-0.0001 (0.0004)	-0.0366 (0.0257)	-0.0027 (0.0013)	-0.0001 (0.0004)

- and it induces no significant change in probabilities for the 40+ week spells. This translates into the prediction that an increase in WBA raises the likelihood that a UI recipient claims all of a spell as unemployment for nonemployment durations of less than 40 weeks. In the case of women, the results for model A indicate the absence of significant UI entitlement effects; so model B excludes all UI benefit variables.

8.3 *Estimation Results for the Division of the Some Unemployment Classification*

Before one can fully explore the implications of these empirical findings, one requires more elaborate information about the variation of ρ within the "some unemployment" category. This involves estimating the way in which the event $\rho \epsilon I_s$ breaks down into the seven sub-events $\rho \epsilon I_{s_k}$, $s_k = s_1, \ldots s_7$. Specifications (8.3) represent the probabilities governing the allocation of ρ across the sub-intervals $I_{s_1}, \ldots, I_{s_7}$.

The forms of these specifications estimated here are quite simple due to the sparcity of observations in the interval $0 < \rho < 1$ and in order to avoid the introduction of a substantial number of parameters. The covariates X_1 and X_2 in (8.3) consist of only constant terms and indicators of UI receipt. In particular, X_1 incorporates the variable δ, and X_2 includes only an intercept term. After considerable exploratory data analysis, no other quantities appear to serve as important determinants of the variation of ρ among the intervals $I_{s_1}, \ldots, I_{s_7}$.

In specifying the splines making up the function $g(\ell, X_2, \alpha)$ in (8.3), one must introduce a modification to account for the fact that ρ falls in various combinations of the intervals with zero probability. We incorporate this modification via the specification

$$\begin{aligned} g(\ell, X_2, \alpha) = & \left[\Phi_1(\ell) - \Phi_0(\ell)\right] \left[\psi d_k + \alpha_{01k} + \alpha_{11k}\ell + \alpha_{21k}\ell^2\right] \\ & \sum_{j=2}^{3} \left[\Phi_j(\ell) - \Phi_{j-1}(\ell)\right] \left[\alpha_{0jk} + \alpha_{1jk}\ell + \alpha_{2jk}\ell^2\right], \end{aligned} \tag{8.4}$$

where d_k is a dummy varible defined below and the coefficient ψ has an assigned value that is large and negative. As in the former specification of g given by (7.5), relation (8.4) expresses g as a linear combination of three splines that turn on and off at 0, 7 and 39 weeks. Thus, the only difference in this specification and the former one concerns the presence of the quantity ψd_k. For values of ℓ in which $\text{Prob}(\rho \epsilon I_{s_k} \mid \rho \epsilon I_s, \ell, X) = 0$, we set $d_k = 1$ (so, ψd_k is

a large negative value); otherwise, we set $d_k = 0$.[31] In addition, because of the numerous instances when probabilities take zero values for the cases $\ell \leq 7$, one cannot estimate three free parameters in the first spline for all cells. In recognition of this situation, we eliminiate the minimal number of coefficients in each cell.[32]

To estimate these specifications of conditional probabilities, we apply a conventional maximum likelihood procedure for the multinomial logit model to compute values for the parameters β and α appearing in formulation (8.3). Our sample consists of observations on ρ for those nonemployment spells in which $0 < \rho < 1$. We estimate separate models for men and for women.

Tables 8.2–M and 8.2–W present parameter estimates for men and women, respectively. The analysis sets all coefficients associated with the cell $I_{s_6} = \{\rho : .70 \leq \rho < .85\}$ equal to zero to establish identification;[33] so no results appear for this cell. Consequently, all probabilities are measured relative to $Pr_{s_6}(\ell, X)/Pr_s(\ell, X)$.

8.4 *Implications of the Empirical Results*

To translate the above empirical findings into implications about the influence of UI policies, Tables 8.3–M and 8.3–W report predictions for time proportion probabilities for various worker types and UI program regimes. These tables present estimates of the probabilities $Pr_i = Pr_i(\ell, X)$ given by (8.2) for $i = n, s_1, \ldots, s_7, a$, which characterize the distribution $f(\rho|\ell, X)$ over the entire range of ρ from 0 to 1. The analysis creates predictions of these probabilities using the estimated specifications of (8.2) and (8.3) described above for models B. The tables report predictions of Pr_i for the three representative worker types and the four prototype UI program regimes described in Section 6.3 (see descriptions (6.6), (6.7) and (6.8)). The reference demographic group assumed in Table 8.3–M is 25-year-old white men

[31] Thus, for the cases $k = s_1, s_7$, $d_k = 1$ when $\ell = 1, 2, 3, 4, 5, 6$. For the cases $k = s_2, s_6$, $d_k = 1$ when $\ell = 1, 2, 3$. For the cases $k = s_3, s_5$, $d_k = 1$ when $\ell = 1, 2, 4$. For the case $k = s_4$, $d_k = 1$ when $\ell = 1, 3, 5, 7, 9$; in addition for this last case, $d_k = -1$ when $\ell = 2$ since the conditional probability equals one.

[32] More specifically, for the case $k = s_1, s_7$, one can incorporate only the intercept coefficient α_{01k}; and for the case $k = s_4$ one can admit only the intercept and the linear coefficients α_{01k} and α_{11k}.

[33] While normalisation on a cell probability that can take a value of zero – which occurs for cell s_6 when $\ell = 1, 2, 3$ – may appear to leave the identification of parameters unresolved, such is not the case due to the implicit restrictions arising from the polynomials in the functions g which force probabilities to follow a simple pattern for the alternative values of ℓ.

TABLE 8.2-M

Parameter Estimates of Time Proportion Probabilities of Interior Cells

Estimates of $Pr_k(l,X)/Pr_s(l,X)$

(Standard Errors in Parentheses)

Name	Variables in X_i	Variables in X_i		
		Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
$Pr(\rho \in I_{s_1} \mid \rho \in I_s)$				
Intercept		3.6610 (1.9468)	-2.0287 (1.1092)	1.7013 (2.0242)
Linear Term			0.1814 (0.1124)	-0.[illegible]8 (0.[illegible])
Quadratic Term			-0.0032 (0.0025)	0.0002 (0.0003)
δ	-1.2023 (0.4760)			
$Pr(\rho \in I_{s_2} \mid \rho \in I_s)$				
Intercept		9.1705 (11.6836)	-0.3084 (0.9738)	1.9429 (2.0407)
Linear Term		-4.0640 (4.7184)	0.0776 (0.1062)	-0.0387 (0.0503)
Quadratic Term		0.4446 (0.4674)	-0.0021 (0.0025)	0.0002 (0.0003)
δ	-1.0188 (0.4485)			
$Pr(\rho \in I_{s_3} \mid \rho \in I_s)$				
Intercept		3.1590 (26.6772)	-1.6498 (1.0073)	-1.4132 (2.6155)
Linear Term		-2.0278 (9.6181)	0.1935 (0.1077)	0.0380 (0.0655)
Quadratic Term		0.2877 (0.8606)	-0.0046 (0.0025)	-0.0002 (0.0004)
δ	-0.0374 (0.3873)			
$Pr(\rho \in I_{s_4} \mid \rho \in I_s)$				
Intercept		-3.2587 (1.9258)	-0.9868 (1.2660)	0.5398 (2.2127)
Linear Term		0.8002 (0.3947)	0.1002 (0.1368)	-0.0114 (0.0547)
Quadratic Term			-0.0028 (0.0032)	0.0001 (0.0003)
δ	-0.2126 (0.4276)			

TABLE 8.2-M (cont.)

Parameter Estimates of Time Proportion Probabilities of Interior Cells

Estimates of $Pr_k(l,X)/Pr_s(l,X)$

(Standard Errors in Parentheses)

Name	Variables in X_T	Variables in X_T		
		Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
$Pr(\rho \in I_{s_s} \mid \rho \in I_s)$				
Intercept		2.8034 (26.6763)	-2.2058 (1.1730)	-0.4280 (2.0913)
Linear Term		-1.8858 (9.6179)	0.1962 (0.1217)	0.0067 (0.0511)
Quadratic Term		0.2735 (0.8606)	-0.0044 (0.0028)	0.00003 (0.0004)
δ	0.6294 (0.3689)			
$Pr(\rho \in I_{s_-} \mid \rho \in I_s)$				
Intercept		2.8011 (1.9922)	-2.1076 (1.0940)	1.1264 (2.5078)
Linear Term			0.1882 (0.1160)	-0.0248 (0.0631)
Quadratic Term			-0.0043 (0.0027)	0.0001 (0.0003)
δ	0.0184 (0.4204)			

TABLE 8.2-W

Parameter Estimates of Time Proportion Probabilities of Interior Cells

Estimates of $Pr_k(l,X)/Pr_5(l,X)$

(Standard Errors in Parentheses)

Name	Variables in X_1	Variables in X_2		
		Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
$Pr(\rho \in I_{s_1} \mid \rho \in I_s)$				
Intercept		0.1423 (1.3759)	-1.0544 (1.1672)	4.8146 (1.6818)
Linear Term			0.2193 (0.1237)	-0.0705 (0.0399)
Quadratic Term			-0.0038 (0.0028)	0.0004 (0.0002)
δ	-1.3863 (0.4078)			
$Pr(\rho \in I_{s_2} \mid \rho \in I_s)$				
Intercept		3.7443 (11.7522)	0.6163 (1.1534)	4.5392 (1.6990)
Linear Term		-0.6852 (4.4537)	0.0968 (0.1246)	-0.0817 (0.0402)
Quadratic Term		0.0137 (0.4163)	-0.0026 (0.0029)	0.0004 (0.0002)
δ	-0.9877 (0.4265)			
$Pr(\rho \in I_{s_3} \mid \rho \in I_s)$				
Intercept		-16.8795 (23.1913)	1.4635 (1.2196)	2.7549 (1.7921)
Linear Term		6.6742 (8.2490)	-0.0797 (0.1311)	-0.0660 (0.0412)
Quadratic Term		-0.6341 (0.7269)	0.0018 (0.0030)	0.0004 (0.0002)
δ	-0.0064 (0.4236)			
$Pr(\rho \in I_{s_4} \mid \rho \in I_s)$				
Intercept		5.8524 (2.5059)	1.1177 (1.2421)	2.4964 (1.9112)
Linear Term		-0.8990 (0.4704)	-0.0114 (0.1356)	-0.0632 (0.0440)
Quadratic Term			-0.0004 (0.0032)	0.0004 (0.0002)
δ	0.0494 (0.4451)			

TABLE 8.2-W (cont.)

Parameter Estimates of Time Proportion Probabilities of Interior Cells

Estimates of $Pr_k(l,X)/Pr_s(l,X)$

(Standard Errors in Parentheses)

Name	Variables in X_1	Variables in X_2		
		Spell Length 1-7 Weeks	Spell Length 8-39 Weeks	Spell Length 40+ Weeks
$Pr(\rho \in I_{s_{\leq}} \mid \rho \in I_s)$				
Intercept		-14.7028 (22.8649)	0.7813 (1.2810)	2.8697 (1.8700)
Linear Term		5.0873 (8.0972)	-0.0087 (0.1399)	-0.0665 (0.0436)
Quadratic Term		-0.4346 (0.7109)	-0.0002 (0.0033)	0.0003 (0.0002)
δ	-0.2433 (0.4595)			
$Pr(\rho \in I_{s_{>}} \mid \rho \in I_s)$				
Intercept		0.1544 (1.5003)	-0.6097 (1.5176)	2.2625 (2.7291)
Linear Term			0.0474 (0.1610)	-0.0516 (0.0723)
Quadratic Term			-0.0011 (0.0037)	0.0002 (0.0004)
δ	0.6009 (0.4488)			

TABLE 8.3-M

Predictions of Time Proportion Probabilities

Nonemployment Duration	Employment History	UI Regime	UI Receipt	Pr_n	Pr_{s_1}	Pr_{s_2}	Pr_{s_3}	Pr_{s_4}	Pr_{s_5}	Pr_{s_6}	Pr_{s_7}	Pr_a
4 Weeks	H_l	All	No	0.26	0.00	0.05	0.00	0.05	0.00	0.06	0.00	0.57
	H_l	R_1,R_2	Yes	0.00	0.00	0.04	0.00	0.09	0.00	0.10	0.00	0.77
20 Weeks	H_l	All	No	0.08	0.06	0.06	0.06	0.05	0.04	0.04	0.04	0.56
	H_l	R_1,R_2	Yes	0.00	0.01	0.01	0.04	0.02	0.04	0.03	0.02	0.82
39 Weeks	H_l	All	No	0.10	0.18	0.12	0.05	0.04	0.05	0.10	0.06	0.30
	H_l	R_1,R_2	Yes	0.00	0.05	0.04	0.04	0.03	0.08	0.09	0.05	0.63
	H_m	All	No	0.23	0.00	0.03	0.00	0.04	0.00	0.05	0.00	0.65
4 Weeks	H_m	R_1,R_2	Yes	0.00	0.00	0.02	0.00	0.04	0.00	0.05	0.00	0.89
	H_m	R_3,R_4	Yes	0.00	0.00	0.02	0.00	0.04	0.00	0.04	0.00	0.90
	H_m	All	No	0.14	0.06	0.07	0.07	0.05	0.04	0.04	0.04	0.49
20 Weeks	H_m	R_1,R_2	Yes	0.00	0.01	0.01	0.03	0.02	0.04	0.02	0.02	0.85
	H_m	R_3,R_4	Yes	0.00	0.01	0.01	0.03	0.02	0.03	0.02	0.02	0.87
	H_m	All	No	0.14	0.16	0.11	0.05	0.04	0.04	0.09	0.06	0.32
39 Weeks	H_m	R_1,R_2	Yes	0.00	0.04	0.03	0.03	0.02	0.06	0.07	0.04	0.71
	H_m	R_3,R_4	Yes	0.00	0.03	0.03	0.03	0.02	0.06	0.06	0.04	0.73

TABLE B.3-M (cont.)

Predictions of Time Proportion Probabilities

Nonemployment Duration	Employment History	UI Regime	UI Receipt	Pr_n	Pr_{s_1}	Pr_{s_2}	Pr_{s_3}	Pr_{s_4}	Pr_{s_5}	Pr_{s_6}	Pr_{s_7}	Pr_a
	H_h	All	No	0.36	0.00	0.02	0.00	0.03	0.00	0.03	0.00	0.55
4 Weeks	H_h	R_1	Yes	0.00	0.00	0.01	0.00	0.02	0.00	0.04	0.00	0.93
	H_h	R_2	Yes	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.96
	H_h	R_3, R_4	Yes	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.96
	H_h	All	No	0.24	0.05	0.06	0.06	0.04	0.04	0.04	0.04	0.44
20 Weeks	H_h	R_1	Yes	0.00	0.00	0.01	0.02	0.01	0.03	0.02	0.01	0.90
	H_h	R_2	Yes	0.00	0.00	0.01	0.01	0.01	0.02	0.01	0.01	0.93
	H_h	R_3, R_4	Yes	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.95
	H_h	All	No	0.18	0.15	0.10	0.05	0.03	0.04	0.09	0.05	0.31
39 Weeks	H_h	R_1	Yes	0.00	0.03	0.02	0.03	0.02	0.05	0.06	0.04	0.76
	H_h	R_2	Yes	0.00	0.03	0.02	0.02	0.02	0.04	0.05	0.03	0.79
	H_h	R_3, R_4	Yes	0.00	0.02	0.02	0.02	0.01	0.04	0.04	0.03	0.82

TABLE 8.3-W

Predictions of Time Proportion Probabilities

Nonemployment Duration	Employment History	UI Regime	UI Receipt	Pr_n	Pr_{s_1}	Pr_{s_2}	Pr_{s_3}	Pr_{s_4}	Pr_{s_5}	Pr_{s_6}	Pr_{s_7}	Pr_a
	H_l	All	No	0.24	0.00	0.06	0.00	0.07	0.00	0.02	0.00	0.61
4 Weeks	H_l	All	Yes	0.00	0.00	0.03	0.00	0.04	0.00	0.02	0.00	0.91
	H_l	All	No	0.29	0.13	0.10	0.04	0.05	0.04	0.02	0.02	0.31
20 Weeks	H_l	All	Yes	0.00	0.04	0.04	0.04	0.06	0.03	0.02	0.04	0.72
	H_l	All	No	0.26	0.24	0.09	0.07	0.03	0.04	0.03	0.03	0.21
39 Weeks	H_l	All	Yes	0.00	0.12	0.07	0.13	0.06	0.06	0.05	0.11	0.41
	H_m	All	No	0.25	0.00	0.06	0.00	0.09	0.00	0.03	0.00	0.56
4 Weeks	H_m	All	Yes	0.00	0.00	0.03	0.00	0.06	0.00	0.03	0.00	0.88
	H_m	All	No	0.42	0.13	0.10	0.04	0.05	0.04	0.02	0.02	0.18
20 Weeks	H_m	All	Yes	0.00	0.05	0.06	0.06	0.09	0.05	0.03	0.05	0.61
	H_m	All	No	0.31	0.24	0.09	0.07	0.03	0.04	0.03	0.03	0.16
39 Weeks	H_m	All	Yes	0.00	0.13	0.08	0.14	0.06	0.07	0.06	0.12	0.35

who are high-school graduates; and Table 8.3–W reports results for 25-year old women who are high-school graduates, unmarried and without children.[34]

Each table reports estimates for several configurations of the covariates ℓ and X: the length of the nonemployment spell ℓ varies in the first column; work histories identified by the three representative worker types change in the second column (with the results for H_ℓ listed first, for H_m second, and for H_h last); the four varieties of policy regimes vary in the third column; and an indicator of UI receipt adjusts in the fourth column. Because the *WBA* is the only UI benefit variable that serves as a significant determinant of the distribution of ρ in the case of men, Table 8.3–M combines predictions for UI policy regimes implying the same value of *WBA* into a single set of results. Thus, for worker type H_ℓ the table combines regimes R_1 and R_2, and it recognizes that this worker is ineligible for UI under regimes R_3 and R_4 and is therefore a nonrecipient. For worker type H_m, the table distinguishes between the *WBA* paid by regimes R_1 and R_2 from that paid by R_3 and R_4. For worker type H_h, the table reports results for the three distinct values of *WBA* paid by regime R_1, by regime R_2 and by regimes R_3 and R_4 available to this worker. Because UI entitlement variables are not significant determinants of the distribution of ρ in the case of women, Table 8.3–W reports predictions merely distinguishing whether an individual collects UI or not. No results appear in this latter table for worker type H_h in recognition of the rarity of this type among women.

The evidence presented in these tables supports two main conclusions. First, UI-recipients always report a substantially larger fraction of their nonemployment spell as unemployment, regardless of the other circumstances. Second, the predicted time proportion distributions for men reveal that unemployment makes up a greater fraction of nonemployment spells as one raises the *WBA* paid by a UI program, but the shifts in these distributions translate into minor effects. For example, movement from regime R_1 to R_3 or to R_4 for worker type H_h boosts his *WBA* from \$150 per week to \$250, and this leads to no more than a .06 change in the "all unemployment" probability. Of course, in the case of women there are no UI-entitlement effects admitted as a consequence of their insignificance in estimation.

[34] As in the previous predictions, individuals are assumed not to have quit their jobs; $EBDUM = 0$; and the variables $UNRATE$ and $UITAX$ as set equal to their sample mean.

9. Relating UI Entitlements and Recipiency

The full impact of UI policies is hidden in the empirical work done so far due to the treatment of recipiency status as an exogenous condition. The empirical findings of the previous sections indicate that the unemployment experiences of individuals who collect UI benefits during times of nonemployment differ quite substantially from the experiences of individuals who do not receive benefits. UI recipiency expands the lengths of nonemployment spells and leads to large changes in the fraction of each spell reported as unemployment. Consequently, even if UI entitlements were found to have no effect in the estimation presented up to this point, it is still the case that UI policies could have a major impact on the amount of unemployment by exerting a big influence on an individual's decision to collect UI and acquire recipiency status.

The importance of UI entitlements in influencing this decision is the topic to which we now turn. The distribution describing recipiency in the previous discussion is $f(\delta|E, T, PA)$, which one may simply write as $f(\delta|X)$ with the covariates X incorporating the variables E, T H, Z, and M.

9.1 *Estimating a Specification for the Recipiency Distribution*

The formulation of $f(\delta|X)$ estimated in the following analysis takes the form

$$f(\delta = 1|X) = Pr(\delta = 1|X) = \frac{1}{1 + e^{X\beta}} \tag{9.1}$$

which, of course, represents a standard logit. The variables making up X include the full set of demographic characteristics introduced in earlier specifications, the bracketed group of work-history variables H_5 given by (7.7), and the macroeconomic and UI-taxation variables listed in (6.4) and (6.5). The analysis incorporates three quantities capturing the influence of UI entitlements on recipiency: the two variables WBA and WE included in the empirical relationships considered above, and the product $WBA * WE$ which represents total UI benefits available to an individual during a nonemployment episode. The following estimation evaluates X at the start of spells.

To estimate the probabilities $Pr(\delta = 1|X)$, we apply maximum likelihood to compute values for the parameters β appearing in specification (9.1). Our sample consists of observations on whether UI collection took place during nonemployment spells associated with

values of X which qualify an individual for compensation from the UI system. Clearly, for spells associated with combinations of X and work-history variables that render a person ineligible for UI receipt, $Pr(\delta = 1|X) = 0$. We estimate distinct models for men and women.

Tables 9.1–M and 9.1–W presents estimates of recipiency probabilities for three configurations of the UI entitlement variables, designated models A, B and C. Model A incorporates three UI-benefit quantities: WBA, WE and $WBA * WE$. Model B deletes the variable $WBA * WE$. Finally, model C retains those quantities that enter as significant determinants of recipiency.

9.2 *Implications of the Empirical Results*

The evidence presented in these tables indicates that the form of UI entitlements constituting the principal determinants of UI receipt differ according to whether one considers men or women. In the case of men, the key variable is the total value of benefits that an individual could collect throughout his nonemployment spell; with this total benefits variable included, both weekly benefit amount and the weeks eligible variables are statistically insignificant. Inspection of the estimates of model C in Table 9.1-M reveals that an increase in total benefits raises the probability of UI recipiency – this is the implication of the negative coefficient on $WBA * WE$. In the case of women, weeks of UI eligibility is the central factor determining UI receipt since WE is the only quantity that enters with statistical significance at conventional levels of confidence. Referring to the results of model C in Table 9.1–W indicates that a woman with a higher WE has a greater probability of collecting UI during a nonemployment episode.

To gauge the importance of UI entitlements on the likelihood of UI recipiency, Tables 9.2–M and 9.2–W report predictions of the probabilities $Pr(\delta = 0|X)$ and $Pr(\delta = 1|X)$ for the representative worker types and UI policy regimes considered in the previous discussion. The predictions come from the estimated specification (9.1), with the covariates X evaluated to identify 25-year-old individuals who are white, high-school graduates, unmarried and without children.

The evidence presented in these tables supports three basic conclusions. First, more generous UI programs encourage the collection of benefits. Second, increases in the probability

TABLE 9.1-M

Parameter Estimates of the UI Reciept Probability

Estimates of $Pr(\delta = 1 \mid X)$

(Standard Errors in Parentheses)

	Model A	Model B	Model C
Log Likelihood	-1023.115	-1025.413	-1024.782
Variable	Estimate	Estimate	Estimate
AGE	-0.9880 (0.4774)	-0.9860 (0.4793)	-0.9721 (0.4780)
EDU	-1.7163 (0.3502)	-1.6967 (0.3483)	-1.7061 (0.3487)
AGE*EDU	0.0493 (0.0164)	0.0486 (0.0164)	0.0490 (0.0162)
AGE^2	0.0062 (0.0108)	0.0064 (0.0109)	0.0060 (0.0108)
EDU^2	0.0296 (0.0114)	0.0296 (0.0116)	0.0296 (0.0114)
RACE	0.3433 (0.1589)	0.3409 (0.1587)	0.3439 (0.1583)
UITAX	-0.4476 (0.1397)	-0.4509 (0.1393)	-0.4528 (0.1385)
UNRATE	-0.0084 (0.0238)	-0.0103 (0.0237)	-0.0109 (0.0235)
EBDUM	-0.3878 (0.1196)	-0.3915 (0.1193)	-0.4073 (0.1180)
WBA	0.0086 (0.0051)	-0.0008 (0.0023)	
WE	0.0163 (0.0159)	-0.0122 (0.0067)	
WBA*WE	-0.0003 (0.0001)		-0.0001 (0.00005)

TABLE 9.1-W

Parameter Estimates of the UI Reciept Probability

Estimates of $Pr(\delta = 1 \mid X)$

(Standard Errors in Parentheses)

	Model A	Model B	Model C
Log Likelihood	-692.853	-693.973	-694.201
Variable	Estimate	Estimate	Estimate
AGE	-0.4801 (0.5579)	-0.5269 (0.5570)	-0.5088 (0.5559)
EDU	-0.5455 (0.4669)	-0.5971 (0.4646)	-0.5861 (0.4644)
AGE*EDU	-0.0288 (0.0229)	-0.0273 (0.0229)	-0.0276 (0.0230)
AGE^2	0.0161 (0.0135)	0.0166 (0.0135)	0.0163 (0.0135)
EDU^2	0.0573 (0.0128)	0.0580 (0.0127)	0.0577 (0.0127)
RACE	-0.1952 (0.2012)	-0.2082 (0.2005)	-0.2005 (0.2004)
MARRIED	-0.2296 (0.1482)	-0.2310 (0.1480)	-0.2305 (0.1480)
NUMKIDS	0.0364 (0.1091)	0.0411 (0.1091)	0.0381 (0.1092)
UITAX	-0.5256 (0.1677)	-0.4982 (0.1649)	-0.4988 (0.1647)
UNRATE	-0.0292 (0.0311)	-0.0270 (0.0311)	-0.0261 (0.0310)
EBDUM	0.2010 (0.1565)	0.1938 (0.1560)	0.1834 (0.1543)
WBA	-0.0081 (0.0083)	0.0024 (0.037)	
WE	-0.0589 (0.0201)	-0.0328 (0.0087)	-0.0332 (0.0087)
WBA*WE	0.0003 (0.0002)		

TABLE 9.2-M

Predictions of the Probability of UI Receipt

Employment History	UI Regime	$Pr(\delta = 0)$	$Pr(\delta = 1)$
H [illegible]	R_1	0.77	0.23
H [illegible]	R_2	0.76	0.24
H [illegible]	R_3	NE	NE
H [illegible]	R_4	NE	NE
H [illegible]	R_1	0.52	0.48
H [illegible]	R_2	0.51	0.49
H [illegible]	R_3	0.50	0.50
H [illegible]	R_4	0.46	0.54
H [illegible]	R_1	0.28	0.72
H [illegible]	R_2	0.25	0.75
H [illegible]	R_3	0.23	0.77
H [illegible]	R_4	0.18	0.82

TABLE 9.2-W

Predictions of the Probability of UI Receipt

Employment History	UI Regime	$Pr(\delta = 0)$	$Pr(\delta = 1)$
H_1	R_1	0.83	0.17
H_1	R_2	0.73	0.27
H_1	R_3	NE	NE
H_1	R_4	NE	NE
H_7	R_1	0.64	0.36
H_7	R_2	0.59	0.41
H_7	R_3	0.59	0.41
H_7	R_4	0.48	0.52

of receipt associated with greater generosity are larger for women than for men; whereas probabilities change as much as .2 in the case of females, changes for men are only about one-half this size. Third, and not surprisingly, the earnings qualifications of a UI program for determining eligibility is a major source of control for effecting the likelihood of recipiency. For example, in the case of men, while programs R_3 and R_4 generally offer greater benefits to those who qualify, their more stringent eligibility criteria sharply curtail UI collection for low-intensity workers.

10. The Impact of UI Policies on the Duration of Unemployment

Combining the estimation results of Sections 7–9 provides the ingredients necessary to answer the question posed at the beginning of Section 6, which one may simply state as: Does the generosity of UI programs influence the amount of unemployment experienced between jobs? The following discussion proceeds in two steps: first, it constructs the distributions of the number of weeks of unemployment that occurs after job separation for UI and non-UI recipients; next, it integrates these results with the likelihood of UI recipiency to infer the full effects of UI policies on the accumulative amount of unemployment experiences.

10.1 *Comparing Unemployment Durations for UI and non-UI Recipient Populations*

One of the most popular distributions analyzed in the literature describes the duration of unemployment that occurs after exiting from a job for individuals who collect UI compensation. Such distributions are typically the focus of studies that use program data. In the framework developed above, the function $f(U|\delta, E, T, PA)$ characterizes the form of this distribution, with $f(U|\delta = 1, E, T, PA)$ describing the experiences of the UI-recipient population. These quantities summarize how the amount of unemployment varies as one shifts UI entitlements within populations selected according to their UI-collection status.

One can infer the properties of this distribution from the results presented in Sections 7 and 8. In particular, as indicated by formula (5.7), one can construct an estimate of $f(U|\delta, E, T, PA)$ by calculating a summation over the distributions $f(\ell|\delta, E, T, PA)$ and $f(\rho|\ell, \delta, E, T, PA)$. The former quantity is simply the nonemployment duration distribution estimated in Section 7, and the second is the time proportion distribution estimated in Section 8.

Tables 10.1–M and 10.1–W provide a general description of the unemployment duration distribution $f(U|\delta, E, T, PA)$ computed using the above procedure for various configurations of the covariates. As before, the designation "M" in the table numbering indicates that the predicted distributions refer to men who are members of the demographic group considered in Figures 7–M and Table 8.3–M, and "W" identifies the results for the comparable group of women. The tables report the 10, 25, 50, 75, 90 and 95 percentiles associated

TABLE 10.1-M

Predictions of the Distribution of Weeks of Unemployment by Recipiency Status

Employment History	UI Regime	UI Receipt	10%	25%	Median	75%	90%	95%
H_1	All	No	0	1	5	12	26	38
H_1	R_1	Yes	2	4	9	16	28	44
H_1	R_2	Yes	2	5	11	21	38	53
H [illegible]	All	No	0	1	3	7	14	23
H [illegible]	R_1	Yes	2	3	8	13	21	30
H [illegible]	R_2	Yes	2	4	8	14	23	33
H [illegible]	R_3	Yes	2	4	8	14	23	33
H [illegible]	R_4	Yes	2	4	9	17	29	41
H [illegible]	All	No	0	1	2	5	12	24
H [illegible]	R_1	Yes	2	3	6	15	29	40
H [illegible]	R_2	Yes	2	3	6	15	29	40
H [illegible]	R_3	Yes	2	3	6	15	29	40
H [illegible]	R_1	Yes	2	3	8	20	37	48

TABLE 10.1-W

Predictions of the Distribution of Weeks of Unemployment by Recipiency Status

Employment History	UI Regime	UI Receipt	10%	25%	Median	75%	90%	95%
H_1	All	No	0	1	3	8	17	29
H_1	R_1	Yes	1	3	6	10	17	25
H_1	R_2	Yes	2	4	8	16	30	49
H_F	All	No	0	1	2	5	12	22
H_F	R_1	Yes	2	3	6	11	20	34
H_F	R_2	Yes	2	3	7	13	24	43
H_F	R_3	Yes	2	3	7	13	24	43
H_F	R_1	Yes	2	4	9	18	42	82

with the constructions of the distribution $f(U|\delta, E, T, PA)$. The first column of the table specifies the work-history variables set according to the three representative worker types: the second column allows for adjustments in the entitlement variables in a way consistent with the four prototype UI policy regimes; and the third column designates whether results refer to a UI or to a non-UI recipient population.

The evidence presented in these tables convey three main findings. First, UI recipients typically experience substantially more weeks of unemployment between jobs than nonrecipients. This follows without exception in the case of men, and holds with only minor qualifications for low-intensity workers in the case of women. Second, changes in the weekly benefit amount offered by a UI program have no appreciable effect on the distribution of unemployment. Whether one considers either men or women, there is literally no difference in the percentiles associated with two distributions that describe the number of weeks of unemployment for two UI policy-regimes that pay different WBA's over the same length of time. Third, changes in the weeks of eligibility offered by a program induce considerable shifts in the distribution of unemployment, especially in that region of the distribution describing long durations. In the case of men, an extension of WE from 26 to 39 weeks leads to around only 1 to 2 more weeks of unemployment for a median individual who collects UI, but unemployment lengthens by 3 to 5 weeks for at least 25 percent of recipients and by 6 to 8 weeks for at least 10 percent of this group. The situation is quite comparable in the case of women except that there is even a more pronounced effect on the longer unemployment durations; the number of weeks of unemployment almost doubles for the top 10 percent of UI recipients.

10.2 *Comparing Unemployment Durations Across Policy Regimes*

One now has sufficient information to evaluate the comprehensive effects of UI policies on unemployment. The distribution $f(U|R, PA)$ quantifies these effects, and one can apply formula (5.6) using the results obtained above to develop estimates of this distribution. For a population at large characterized by the attributes PA, knowledge of $f(U|R, PA)$ determines the extent to which weeks of unemployment experienced between jobs adjusts in response to shifts in UI policy. The measured response implied by $f(U|R, PA)$ recognizes that UI

receipt is an endogenous choice which may itself be dependent on the nature of the shift in UI policies.

Tables 10.2–M and 10.2–W characterize the properties of the distribution $f(U|R, PA)$ estimated using formula (5.6) and the empirical results reported in Sections 7–9. In presenting these implications, the population characteristics PA choosen as points of evaluation are the same as those assumed in previous predictions, which describe the behavior of a population consisting of 25-year old men or women who are white, high-school educated, unmarried and without children, who did not quit their job, and who live in a state with average unemployment and UI taxes. The first column of Tables 10.2 identifies the three representative worker types, and the second column designates the four UI policy regimes. The last group of columns report the 10, 25, 50, 75, 90, and 95 percentiles associated with the estimated distributions $f(U|R, PA)$.

The predictions of the comprehensive effects of UI programs presented in these tables highlight two major conclusions of this analysis. First, the size of the WBA paid by a UI program does not influence the number of weeks of unemployment reported between jobs. Second, a rise in the value of WE offered by a program does not alter the allocations of short durations of unemployment, but it makes the longer durations even longer by an increasing amount. These findings essentially mirror those described above in Tables 10.1 which distinguish results by UI recipiency status. Tables 10.2 show that there is no perceptable change in distribution of unemployment experienced by the nonemployed as one moves from a state with a low WBA to one with a high WBA, even when this increase boosts benefits by as much as \$100 per week (for a high wage worker). Further, these tables show that unemployment distributions shift markedly beyond medians in a way to lengthen all durations greater than these points by an ever increasing amount when a state's UI program expands WE.

TABLE 10.2-M

Predictions of the Distribution of Weeks of Unemployment

Employment History	UI Regime	10%	25%	Median	75%	90%	95%
H_l	R_1	0	2	6	14	27	39
H_l	R_2	0	2	7	15	29	43
H_l	R_3, R_4	0	1	5	12	26	38
H_m	R_1	0	2	4	10	18	27
H_m	R_2	1	2	5	11	20	29
H_m	R_3	1	2	5	11	20	29
H_m	R_4	1	2	6	12	24	35
H_h	R_1	1	2	5	12	26	38
H_h	R_2	1	2	5	12	26	38
H_h	R_3	1	2	5	13	26	38
H_h	R_4	1	3	6	17	34	46

TABLE 10.2-W

Predictions of the Distribution of Weeks of Unemployment

Employment History	UI Regime	10%	25%	Median	75%	90%	95%
H_1	R_1	0	1	3	8	17	28
H_1	R_2	0	1	4	10	21	35
H_1	R_3, R_4	0	1	3	8	17	29
H [illegible]	R_1	0	1	4	8	16	28
H [illegible]	R [illegible]	0	1	4	9	19	34
H [illegible]	R_3	0	1	4	9	19	34
H [illegible]	R [illegible]	0	2	5	13	31	61

11. A Synthesis of the Empirical Findings and Closing Remarks

The empirical analysis of the previous sections offers a simple picture of the role of UI policies on both the amount of time that youths spend between jobs and the extent to which they classify this time as unemployment. The following discussion summarizes this picture and relates it to other results in the literature.

11.1 *Summary of the Findings*

For men, the above analysis indicates that an individual who collects UI compared to one who does not is likely to experience a longer spell of nonemployment, at least up to the exhaustion of UI benefits, and to categorize a larger fraction of this spell as unemployment. In total, UI recipients report more weeks of unemployment before returning to jobs.

Regarding the influence of UI entitlements on the experiences of men, these benefits alter individuals' activities through several routes. Concerning the effect of a rise in the weekly benefit amount paid by a program, the results show slight increases in recipiency and in the fraction of a nonemployment spell listed as unemployment; but this rise in *WBA* has essentially no effect on either the length of nonemployment spells or on the number of weeks of unemployment, irrespective of whether one considers the population at large or only the population of UI recipients. Turning to the effects of an increase in the weeks of eligibility offered by a program, this policy shift induces only a minor rise in the likelihood of recipiency, as is the case for an increase in *WBA*. However, in sharp contrast to the effects of *WBA*, an extention of *WE* lengthens both nonemployment spells and the amount of unemployment that occurs between jobs both for UI recipients and for the population at large. This extention does not influence short durations of either nonemployment or unemployment, but it leads to an expansion of the longer durations with the highest durations being stretched out the most.

The findings summarized above for young men also apply for describing the situation for young women with only two exceptions. First, while female UI recipients experience more unemployment than nonrecipients at least up to the point of benefits exhaustion as in the case for men, there is some ambiguity as to whether a similar relationship exists for women when comparing lengths of nonemployment spells. Second, the weekly benefit

amount does not even play a slight role as a factor influencing women's experiences. In contrast to men, changes in *WBA* has no effect on the fraction of a nonemployment spell reported as unemployment, nor does it effect the likelihood that a women collects UI benefits. Whereas total UI benefits serve as the primary measure of UI entitlements determining UI recipiency status for men, the results for women indicate that only weeks of eligibility matter. Other than these two relatively minor exceptions, the influences of UI policies on women's experiences between jobs in nonemployment and in unemployment follow the same pattern as those outlined above for men.

11.2 *Comparision with Results in the Literature*

Relating our findings to those in other studies requires adjustments for differences in definitions of key variables, in empirical approaches adopted to develop results, and in sample compositions. Definitions of such variables as unemployment duration and UI entitlements vary considerably in the existing body of research. The largest group of studies relies on program data and defines unemployment as UI collection and duration as the number of weeks of UI receipt. Other studies use survey data and define unemployment more in accord with the CPS concept and duration as spell length which corresponds to an uninterrupted sequence of weeks. With regard to the notion of entitlements, program-data studies analyze the effects of both the weekly benefit amount and weeks of eligibility to capture the influence of UI policies, whereas survey-data studies consider only the weekly benefit amount as a measure of UI entitlements. The analysis presented here is entirely unique for it uses a definition of unemployment corresponding to one found in survey-data studies, a definition of the full complement of UI entitlements such as the one adopted in program-data studies, and a definition of duration representing the total amount of unemployment that occurs between jobs regardless of the number of spells involved in accumulating this total which is distinct from the ones used in other work.

Concerning differences in empirical approaches, the interpretation of what is meant by a UI effect varies across studies depending on the particular econometric framework applied to obtain estimates and on the sorts of variables incorporated to control for contaminating sources of variation. Some analyses estimate effects via a simple regression model in

an attempt to measure movements in average durations, while other studies use transition-probability frameworks to determine the influence of UI on hazard rates. A necessary econometric feature needed to measure UI-entitlement effects reliably involves recognition of the important interactions among UI benefits and duration, thus creating a framework that permits the influence of UI programs to affect unemployment in a nonuniform manner varying with duration length. While a few program-data studies implement estimation approaches incorporating elementary versions of these interactions, this study is the first to do so using survey data. Further, to ensure that variation in UI benefits in estimation reflects differences in the generosity of UI policies rather than movements along UI schedules, an empirical procedure must in theory incorporate elaborate controls to account for those aspects of individuals' earnings histories that go into the computation of entitlements. Previous studies include only a subset of these controls, with none accounting for a set that is nearly as extensive as the one used in the empirical analysis presented here. Finally, to obtain reliable estimates of UI effects, an empirical approach must account for distinctions in the unemployment experiences of UI recipients versus nonrecipients and for the endogeneity of the choice to collect UI. Without admitting such distinctions, one cannot predict a variety of effects arising from alterations in UI programs, including comprehensive effects characterizing the influence UI policies on a nonemployed population considered in total. The empirical analysis of this report fully recognizes these distinctions and provides predictions of the role of UI on several aspects of nonemployment experiences. In contrast, program-data studies model only behavior associated with the unemployment of UI recipients, and survey-data studies entirely ignore the concept of recipiency status almost without exception.

Turning finally to differences in sample compositions, there are obvious qualifications requiring consideration in relating the findings presented here to those of other studies. The results obtained above describe the nonemployment activities of a young population, with men and women analyzed separately. Program-data studies restrict analyses to recipient populations of all ages; some consider only men, and other combine men and women. Survey-data studies investigate the experiences of a wide range of populations.

While a direct comparison of the findings obtained in this report with those available in

the literature necessarily involves some ambiguities due to the differences cited above, there is value in undertaking such an exercise to place the results of the current study into context. The subsequent discussion carries out this exercise, first focussing on the estimated effects associated with the *WBA* portion of UI entitlements and then proceeding to an analogous comparison of the effects attributed to the *WE* portion.

Both program-data and survey-data studies offer predictions of the influence of the *WBA* on unemployment durations. Recent results based on program data generally suggest that a rise in the *WBA* induces an increase in weeks of unemployment, with a 10% raise in *WBA* predicted to generate anywhere from a 0.5 to a 2 week lengthening of insured unemployment.[35] Within the framework presented in this report, such a forecast most closely corresponds to the effect of *WBA* on the distribution $f(U|\delta = 1, E, T, PA)$. In sharp contrast to predictions of the program-data studies, the findings outlined in Section 10.1 indicate that changes in the *WBA* have no perceptable effect of this distribution. Of course, there are a variety of potential reasons for explaining this discrepancy, including the nontrivial observation that U in program data measures weeks of UI receipt instead of CPS-type unemployment. In studies relying on unemployment measures defined more in tune with the empirical analysis of this report (i.e. CPS-type measures), the evidence of the effects of the *WBA* on unemployment durations is far less conclusive. This evidence, based on various forms of survey-data, often reveals no significant effects of *WBA* on $f(U|\delta = 1, E, T, PA)$ or, more typically, on the distribution $f(U|R, PA)$.[36] These findings agree with the results obtained in Sections 10.1 and 10.2.

Only program-data studies offer a source for comparing predictions of the influence of *WE* on unemployment durations; no survey-data studies of which we are aware account

[35] This range of estimates comes from the studies of Classen (1979), (who predicts a 1-2 week increase), Newton and Rosen (1979) (who predict a 1–8 week increase), Moffitt (1985) (who predicts a 0.5 week increase) and Katz and Meyer (1988b) (who predict a 1–1.5 week increase). Hammermesh (1977) in his review of twelve U.S. studies concludes that the best prediction of the effect of a 10-percentage point increase in the gross replacement rate is a 0.5 week increase in insured unemployment.

[36] Barron and Mellow (1981), using a supplement of the CPS find that *WBA* becomes insignificant once one accounts for recipiency status. Clark and Summers (1982), using the CPS, obtain insignificance of *WBA* on transitions out of either unemployment or nonemployment, which are the transitions relevant for comparing the estimates presented in this report. Katz and Meyer (1988a), using a survey supplement to a program-data source, also find that *WBA* plays an insignificant role in these transitions.

for the effects of WE in estimation. Results from program data suggest that a 1 week increase in WE leads to a lengthening of insured unemployment somewhere in the 0–1 week range, evaluated for an "average" UI recipient.[37] The findings presented in this report fit within this range as long as one interprets the notion of an average individual broadly. Inspection of the results in Section 10.1 describing the impact of WE on the distribution $f(U|\delta = 1, E, T, PA)$ – which most closely approximates the effects obtained using program data – reveals that a 1 week increase in WE generates only about a 0.1 week lengthening of unemployment duration for the median nonemployment episode. For the longer episodes, however, the implied lengthening amounts to about 0.6 weeks. These predictions are clearly in general agreement with those advanced in the literature regarding the influence of WE on unemployment.

11.3 *Policy Implications*

The findings of this report suggest several implications concerning the role of UI policies on the amount of unemployment. At the most basic level, the results indicate that features of UI programs that change the size of weekly benefit amounts are not likely to affect unemployment, whereas features that alter the amount of weeks of eligibility are likely to shift unemployment for those individuals who experience the longer durations. Thus, changes in the maximum level of weekly benefits paid by a program can be expected to have no effect on unemployment. In contrast, the introduction of extended benefit programs can be expected to lead to greater unemployment with a more uneven distribution of experiences across nonemployed persons.

At a more subtle level, these implications highlight the importance of eligibility qualifications in UI programs. A casual comparison of UI regimes across states reveals that those programs paying higher benefits also apply more stringent qualification requirements. Such programs in effect offer higher weekly benefit amounts to those persons who qualify and at the same time assign zero weeks of eligibility to a greater fraction of the nonemployed population. Consequently, these programs are likely to induce less unemployment according

[37] This range of estimates comes from the studies of Classen (1979) (who predicts no significant effect), Newton and Rosen (1979) (who predict a 1 week increase), Moffitt (1985) (who predicts a 0.15 week increase), and Katz and Meyer (1988b) (who predict a 0.20 week increase).

to the implications cited above because the higher *WBA* paid by a program yields no change and the lowering of *WE* reduces the amount of unemployment.

A critical factor ignored throughout this discussion concerns the potential influence of UI policies on the work experiences of individuals. The conclusions drawn above presume that characteristics of UI regimes do not induce persons to change their employment activities. If this presumption is false, then policy shifts, such as increases in the weekly benefit amounts, can lead individuals to alter their worker-type classifications or to enter nonemployment when they would not otherwise. Such changes in work histories imply a different set of unemployment experiences according to the findings of this report. Developing an empirical framework to account for these possible work-experience effects of UI policies is not as difficult as one might expect. One can accomplish this task by adding an empirical model describing the earning and the job separation experiences of individuals while employed to the model outlined in Sections 5–9, which essentially makes work histories endogenous variables. We hope to pursue such an objective in future research.

APPENDIX A: Construction of a Data Set from the YNLS Describing Earnings and Employment Experiences

In this appendix the procedures used to construct data on earnings and employment are described. These data are used both to describe the earnings and employment experiences of youth, and in the subsequent analysis of unemployment insurance.

The YNLS data are briefly discussed. There follows a very detailed discussion of data derivation. Then the samples used in Section 3 are defined and discussed. It is established that while in any calendar year earnings data are usually available for at least one job, earnings data are often not available for all jobs. This is not so critical for Section 3, where incomplete earnings data may lead to only specific calendar years being dropped from the analysis. It is very critical for the unemployment insurance analysis which requires that earnings data be complete in all calendar years. Since earnings data are most often missing on less important "intermittent" jobs, these missing data are imputed by methods described at the end of this appendix.

The discussion is quite detailed. To understand the body of this appendix, it is sufficient to read only Sections A.1 and A.5, which are self-contained.

A.1 *General Considerations*

The data used come from the first seven rounds of the National Longitudinal Survey of Youth (YNLS). This survey commenced in 1979, when the respondents were between 14 and 22 years old. Calendar year data can be constructed for the seven years from 1978 to 1984. In this study the first year, in which there is relatively more missing data, is not analyzed.

To avoid confusion about whether a quoted year is the calendar year under investigation, or the interview year from which data is obtained, interviews are referred to by the survey round number rather than the year. Survey Round 1 was conducted in 1979, Survey Round 2 in 1980 and so on.

The primary data source is the YNLS Data Tape. The version used is the public-use multi-file format tape for rounds 1 to 7 combined. In addition, the YNLS Work History Tape is used. This is also publicly available, but this study uses a pre-release version which differs from the public-release Work History in the following minor respect. To conserve space the

public-release version omitted data for the sixth through tenth job held since the previous interview. The pre-release version has data on all ten jobs. (In the public-release version, the A and DUALJOB arrays still use information on up to ten jobs, but to get data on jobs 6 through 10 will require use of the ADDJOBS files, which are available for most but not all years. At each interview between 25 and 47 of the 12,686 cases have more than five jobs.) For geographical information, the Geocode tapes are used.

The complete sample of 12,686 people includes non-random samples of the poor and military personnel. However, this study uses only the 6,111 people in the cross-section sample, designed to represent the noninstitutional civilian segment of youth aged 14 to 21 as of January 1, 1979. Otherwise there are few restrictions on the sample, and every effort is made to keep sample sizes as large as possible. In particular, only minimal attempts are made to clean or omit suspect data. One exception is that start and stop dates for jobs and gaps within jobs are checked for validity.

A.2 *Work History Data*

The analysis is based on data on each job held since the last interview. This is obtained in the Employer Supplements and the "On Current Labor Force Status" section of the main questionnaire. This data is stored in a convenient form in the YNLS Work History Tape, which has weekly activity arrays that give codes for every employer in that week, or if the respondent is not employed the major activity. Weekly data on labor supply and earnings can be obtained.

These data are aggregated to form calendar year data. The calendar year data will typically use data from the two interviews that together span that calendar year. For example, calendar year 1981 computed earnings will generally use data from both the 1980 and 1981 interviews (but will use other interviews if one or both of these interviews are missed).

A major task is to determine which respondents should be omitted due to missing data. The term "missing" data encompasses the following situations:

(1) Data cannot be obtained due to noninterview.

(2) Received income from military service.

(3) Data cannot be obtained due to age 15 years or less (every job is obtained only for

respondents 16 years or older).

(4) Job dates given are inconsistent; e.g. stop before start.

(5) Data cannot be obtained due to falling into a class that is not asked the relevant questions; e.g. wage rates are not obtained for all jobs. (These are coded as −4 in the raw data.)

(6) Missing in the sense used in the YNLS: the respondent was asked the question but refused to answer (−1) or did not know (−2), or should have been asked the question but was not (−3).

Most data are "missing" for the first five reasons.

A.2.1 *Data on Each Job in Each Week*

For all respondents 16 years and over, detailed information is obtained for every "regular" civilian job held since the previous interview. This information includes the dates the job started and stopped; within this, dates for periods during which the respondent did not work for the employer; hours per week usually worked at the job; and the usual wage rate. Unfortunately, the wage rate is not obtained for every job.

In many instances a respondent will be working for the same employer at different interviews. A code exists to link jobs with the same employer across interviews. To avoid confusion the following terminology is used. Data on a job is obtained directly from the job data at each interview. Data on an employer is obtained by linking different job entries from different interviews for the same employer. Most of the analysis in this study is done at the job level, i.e. the fact that different jobs from different interviews may be with the same employer is ignored.

The key variables are based on the following definitions, drawn from the YNLS questionaire:

Job:

"Some jobs are odd jobs – that is, work done from time to time, like *occasional* lawnmowing or babysitting. Others are *regular* jobs – that is, jobs done on a more or less regular basis. (Not counting the job you had last week), Since (DATE OF LAST INTERVIEW), have any jobs you've had for pay been done on a more or less regular basis? Please give me the names

of each of your employers for all *regular* jobs you've had for pay since (DATE OF LAST INTERVIEW) (not counting the job you had last week)."

Additional questions are asked to ensure recording of all jobs for pay with government sponsored programs such as college work-study, high school cooperative work-study, Neighborhood Youth Corps In-School, summer employment, and employer tax credit.

The job last week is the job picked up in the "On Current Labor Force Status" section of the main questionnaire, where questions virtually the same as those in the monthly CPS are asked. In particular, the respondent is asked to report any work at all last week, not counting work around the house, and to give details for the employer with whom the respondent worked the most hours last week. This job may be either occasional or regular. (About 5 percent of the CPS jobs are occasional rather than regular in Surveys Round 3 to 6 for the full sample of 12,686).

Note, for the items below, the respondent is asked "For *all* of the *rest* of the questions we have about (EMPLOYER), please think only of the time you worked for (EMPLOYER) since (DATE OF LAST INTERVIEW).

Gaps within Jobs:

"For one reason or another, people often do not work for a week, a month, or even longer. For example, strikes, layoffs, and extended illnesses can cause people to miss work for a week or longer. Between (DATE STARTED JOB / LAST INTERVIEW) and (DATE STOPPED JOB / NOW), were there any periods of a full week or more during which you did *not* work for this employer, not counting *paid* vacations or *paid* sick leave?"

Up to 4 such gaps are reported.

Hours per week:

"How many hours per week (do/did) you *usually* work at this job?"

Wage:

"Altogether, including tips, overtime, and bonuses, how much (do/did) you *usually* earn at this job? Please give me the amount you earn(ed) *before deductions* like taxes and Social Security (are/were) taken out. Was that per hour, per day, per week, or what?"

The wage is reported as hourly, daily, weekly, bi-weekly, monthly and annual. The wage rate question is only asked if one or more of the following conditions are satisfied: (1) The job is the current job recorded in the CPS section. (2) The job is part of a government-sponsored program. (3) The job has been held for more than 9 weeks and is for 20 or more hours per week and the respondent is 16 years and older. Thus wages for intermittent jobs are missing.

The necessary jobs-related data from the Employer Supplements are stored on both the original raw YNLS data set, and the YNLS Work History Tape. The latter is used here as the data are stored as an easily accessed PL/I data structure. In addition, the Work History tape has useful constructed variables such as the A and DUALJOB arrays described below. The Work History tape is accompanied by documentation that includes a listing and description of the PL/I program that created the work history tape.

The work history program uses the raw data on start and stop dates for jobs, and start and stop dates for gaps within jobs, to construct weekly activity arrays, called the A and DUALJOB arrays, which detail every job that the respondent had that week. (For those who had no civilian job, additional data from the "Military" and "Gaps when R was not Working or in the Military" sections are used, and the arrays indicate whether the person was in the active armed services, or unemployed or out of the labor force).

The dates are originally entered to the day. Employment in any day of a week is treated as employment for the whole week. For example, a job that begins on a Wednesday is treated as beginning on the previous Sunday, and a job that ends on a Wednesday is treated as ending on the following Saturday. If job start and stop dates are randomly distributed across the week, the length of employment at each job will on average be overstated by a week. However, the bias is nowhere near as great as this for the following reasons. A disproportionate number of jobs begin on a Monday and end on a Friday. For jobs from

different survey rounds associated with the same employer, the problem arises only for the start date of the job in the first survey that the employer is recorded and the stop date of the job in the last survey that the employer is recorded. The start and stop dates for gaps within jobs are similarly treated, which imparts a potential bias in the opposite direction.

A detailed description of the program that constructs jobs data from the YNLS Work History Tape follows. Access to documentation for this data set is assumed.

Hourly Wage and Weekly Wage for Each Job:

If the job is not for pay, the Work History program sets HOURLYWAGE to –4. This needs to be recoded to zero. If CLASSWORKER equals 4 and (PAYRATE equals 0 or TIMERATE equals –4) then HOURLYWAGE equals 0. For Rounds 1 to 7 there are a total of 105 such jobs.

The weekly wage is constructed in the obvious fashion. If HOURLYWAGE >= 0 and HOURSWEEK > 0 then WEEKLYWAGE equals HOURLYWAGE times HOURSWEEK. This algorithm can compute WEEKLYWAGE only if HOURSWEEK is reported. In some cases it is possible to construct WEEKLYWAGE even if data on HOURSWEEK are missing. This is the case when wages are reported as weekly (then WEEKLYWAGE = PAYRATE), bi-weekly (then WEEKLYWAGE = PAYRATE / 2), monthly (then WEEKLYWAGE = PAYRATE / 4.3) and yearly (WEEKLYWAGE = PAYRATE / 52). These calculations are done only in those cases where HOURSWEEK is missing. For rounds 1 to 7 there are a total of 105 such jobs. WEEKLYWAGE is truncated to the nearest cent.

In the Work History program, HOURLYWAGE is truncated to the nearest cent. This makes no difference if wages are reported at an hourly rate, the case for half the reported wages. But for wages reported as daily, etc. the hourly wage and weekly wage will be slightly understated.

Missing Data Because Not Interviewed:

If the respondent misses one or more rounds of the survey, but is interviewed at a later round, data are not missing, since all the necessary questions are asked for the period since

the last interview. If the respondent is not interviewed at a later round, then data are set to missing for weeks subsequent to the week of the last interview.

Missing Data because Active Military Service:

The Work History Tape includes start and stop dates for each period of active service in the military. Active service is service in the branches coded 1 to 4 in the "Military" section of the questionnaire; viz. army, navy, air force, marine corps. It does not include any of the Reserves or National Guards. The dates are used rather than a code of 7 in the A array, as when a person in the military also holds a civilian job the A array records the job rather than military service. For weeks in which the respondent is in the active services, data are set to missing.

Missing Data because Bad Dates:

The constructed data are based on the A and DUALJOB arrays. These only include jobs for which valid start and stop dates are available. If the dates are invalid, there is no record of the job in the A or DUALJOB array, and no indication that the job is missing. Similarly, if the dates for gaps within jobs are invalid, there is no indication of the gap, and no indication that the gap is missing. (Though for the first gap there is a record, the A array being set to 3). For weeks in which dates for jobs or gaps within jobs are invalid, annual computed earnings are set to missing. Also, more stringent tests of date validity are used.

A respondent is treated as having a job if START > -4 or STOP > -4, and having a gap within jobs if WEEKSNOTWORKED $\neq 0$ and WEEKSNOTWORKED $\neq -4$. Dates for jobs are invalid for the following reasons:

(1) START > STOP +1 or START < 0 or STOP < 0.

(2) START < LASTINT −1 or STOP > INT +1.

(3) PERIODSTART > PERIODSTOP or PERIODSTART < 0 or PERIODSTOP < 0.

(4) PERIODSTART < START −1 or PERIODSTOP > STOP +1.

In the first round, some of the dates for gaps within jobs are associated with the wrong job. This is an error in the YNLS Data Tape that will be detected by the above tests (in many cases), and the additional reasons for rejection:

(5) PERIODSTART >= 0 or PERIODSTOP >= 0 when WEEKSNOTWORKED equals 0 or −4

(6) PERIODSTART >= 0 or PERIODSTOP >= 0 when START = −4 or STOP = −4.

The Work History program does only checks (1) and (3). The presence of the "+1" or "−1" terms in the above tests may at first seem strange. It is necessary because of the way dates are treated for jobs held at the interview date. For example, if the respondent ended a job on 1/10/79 and was interviewed on 1/12/79, then STOP = CEIL(375/7) = 54 and INT = FLOOR(377/7) = 53, in which case STOP > INT even though the dates are obviously valid. See "Description of the NLSY 1979–1985 Work History Program" and the program itself, for further details on its treatment of dates.

If the data fail the checks above, job dates are treated as being invalid from LASTINT to INT, or in the case of checks (4) and (5) from START to STOP. Data are set to missing for the weeks that these dates lie in. Typically two calendar years will be effected.

Missing Data because of Missing Wage:

As already noted, wage rates are not obtained for all intermittent jobs. The percentage of jobs for which the wage rate was deliberately not requested ranges from 29 percent in Round 1 down to 19 percent in Round 7. In these cases the job is one held for less than 9 weeks and for less than 20 hours per week. For an additional 2 percent of all jobs, wage rates are missing due to refusal, don't know, invalid skip, or code 7 for time unit rate of pay.

A.2.2 *Weekly Earnings and Work Experiences*

Weekly hours (WH) and weekly earnings (WE) from all jobs this week are obtained by summing usual hours per week and earnings per week over each job recorded in the weekly A and DUALJOB arrays. Hourly earnings this week (WE/WH) is simply computed as WE divided by WH.

In section 3 variation in WH, WE and WE/WH over weeks in the calendar year is studied. The calendar year is standardized at 52 weeks. Weeks are allocated to the years 1978 through 1984 using the scheme described below in Section A.2.3.

A.2.3 *Annual Computed Earnings and Work Experiences*

To obtain annual work experience or earnings data the basic approach is the following. From the A and DUALJOB arrays obtain the number of weeks in each calendar year at each job. Multiplying by each job's hours per week or earnings per week and summing across jobs yields annual hours (AH) or annual computed earnings (ACE).

To make ACE comparable with annual reported earnings (ARE, defined below) the calendar year length for ACE and AH is determined by the number of work days.

When a week spans two calendar years, jobs in that week are allocated partly to each year, according to the proportion of the work week (Monday to Friday) falling into each. Weeks begin on a Sunday, with week 1 commencing on 1/1/78. The calendar years are:

1978: Weeks 1 to 52.

1979: 53 to 104 and 0.2×105.

1980: 0.8×105 and 106 to 156 and 0.6×157.

1981: 0.4×157 and 158 to 208 and 0.8×209.

1982: 0.2×209 and 210 to 261.

1983: 262 to 313.

1984: 314 to 365 and 0.2×366.

Each calendar year is processed in turn, using the A and DUALJOB entries for the weeks in that particular year to compute the number of weeks in each job held that calendar year. Only job entries in the A and DUALJOB arrays are processed. In particular, code 3 in the A array is ignored here. It is picked up as missing data at a later stage.

For example, consider the following A and DUALJOB entries:

Weeks	150–170	171–190	191–210
A	201	301	302
DUALJOB	202	302	0

Then in calendar year 1981 there are 13.4 weeks at job 201, 13.4 weeks at job 202, 20.0 weeks at job 301, and 38.8 weeks at job 302.

For each job held in the calendar year, annual earnings are computed in whole dollars as the product of the weekly wage and the number of weeks at the job, divided by 100 and

truncated to an integer value. Then sum over all jobs.

Continuing the earlier example suppose the weekly wage for job 201 is 8000 cents, for job 202 is 22490 cents, for job 301 is 11100 cents, for job 301 is 9500 cents, and for job 302 is 25704 cents. Then for calendar year 1981:

$$\begin{aligned}\text{Computed earnings} &= \text{FLOOR}(8000 \times 13.4/100) + \text{FLOOR}(22490 \times 13.4/100)\\ &+ \text{FLOOR}(11100 \times 20.0/100) + \text{FLOOR}(25704 \times 38.8/100)\\ &= 1072 + 3013 + 2220 + 9973\\ &= \$16,278\end{aligned}$$

For computed earnings to be comparable with the reported earnings data, the reported wage for each job in each calendar year should be the average wage for the job that calendar year.

Since the reported wage is the usual wage received over the period worked since the last interview, this will be the case on average for respondents interviewed on January 1 each year. There will be no bias.

For respondents interviewed at other times, the reported wage for each job will not be the average for the calendar year. But this will not induce any biases. To see this, consider the following simple example. The respondent works for only one employer, with the weekly wage path:

	Jan–Mar	Apr–Jun	Jul–Sept	Oct–Dec
1981	\$200	\$210	\$220	\$230
1982	\$240	\$250	\$260	\$270
1983	\$280	\$290	\$300	\$310

The average weekly wage for calendar year 1982 is \$255, and reported earnings will be 52 times \$255. Suppose the respondent is always interviewed on March 31. Then at the Round 4 survey on March 31, 1982 he should report a usual weekly wage of \$225 (the average of \$210, \$220, \$230, \$240), and at the Round 5 survey on March 31, 1983 a usual weekly wage of \$265 should be reported. Computed annual earnings are 13 times \$225 plus 39 times \$265, which equals 52 times \$255, as desired. Again there is no bias.

There are clearly cases where there will be individual biases, due to jobs held only in the first few weeks after or before an interview, or interviews not in the same month each year, or interviews missed entirely. But there is no *a priori* reason to believe that these will not balance out over all jobs and respondents.

Annual weeks worked (AWW) is the number of weeks in the calendar year for which a job is recorded in the weekly A array. AEMPS is the number of employers in the calendar year, obtained by summing over jobs held in the year but not double-counting jobs with the same employer. (Recall that work for an employer may appear as two jobs this year - one from the survey this year and one from the survey next year).

Annual weeks with a multiple job (AWMJ) is the number of weeks in the calendar year for which a job is recorded in both the A and DUALJOB arrays. The work history data are cleaned up to avoid spurious double counting in the survey week - in some cases the work history data records both the entry from this survey and the entry from the next survey.

A.3 *Annual Reported Earnings*

In the "On Assets and Income" section of the questionnaire, all respondents are directly asked the amount received from various income sources for the calendar year preceding the interview date. In this paper, annual reported earnings (ARE) are the sum of wage and salary earnings and own farm or business earnings.

Respondents are generally interviewed in the early part of the year. About half the interviews take place in January or February, and over 90 percent of interviews are completed by the end of April. The latest interview month is August. So the recall period for the reported earnings questions is not too long.

The key variables are based on the following definitions:

Wage and Salary Earnings:

"During 19xx, how much did you receive from wages, salary, commissions, or tips from all jobs, before deductions for taxes or anything else?" (Not counting any money you received from your military service).

Own Farm or Business Earnings:

"During 19xx, did you receive any money in income . . . from your own farm? from your own nonfarm business, partnership or professional practice?"

Construction of this variable is straightforward. It is the sum of the two components. The only complication is for those respondents in Rounds 1 to 4 who satisfied all of the following: under 18 years, never married, never had a child, never enrolled in college and lived at home. These respondents were asked a shorter set of income questions. Separate questions were asked for whether or not the respondent received income from (A) working on own business or farm and (B) interest on savings or any other income received periodically or regularly, not counting allowances from parents. However, these respondents were then asked the amount received from A and B combined. For these people data are treated as missing if the answer is yes to both A and B. At most 30 respondents in each of Rounds 2 to 4 are missing earnings data for this reason.

The main reasons for missing data on reported earnings are that the person was not interviewed, or that earnings from service in the military were reported. (There is a separate question asked: "Did you receive any income from service in the military?" If the response is yes or missing, reported earnings are treated as missing that year. This separate question is not asked in the shorter set of questions mentioned in the previous paragraph, but respondents asked the shorter set are unlikely to be in the military, and if they are, they may still be picked up as such in the computed earnings section).

The amount received from each source of income is truncated at $75,001 for rounds 1 to 6, and at $100,001 for Round 7. This occurred for 1 respondent in Round 4, and 4 respondents in each of Rounds 5, 6 and 7. In these instances, data are treated as missing. Note that it is still possible for reported income to exceed $75,001 (or $100,001) if each component is not truncated. Data are also missing if the person was (erroneously) not asked or did not reply to questions on either or both of the components of reported income. Most of this was due to the respondent not knowing the amount received from wages and salary.

A.4 *School Attendance and Education Level*

Data on shcool attendance and educational level can be constructed for each calendar year. However, the school data are much more complete from the Round 3 survey on. In

particular, before 1980 it can be determined that a respondent did not attend school at any time in the year, but for those who did attend at some time the length of school attendance cannot be determined without further assumptions.

The school data come directly from questions in the "Regular Schooling" section about attendance since the preceding interview at regular school: elementary school, middle school, high school, college or graduate school. Some questions about other types of schools and training programs are asked elsewhere but are not used here.

Monthly school attendance data are often, but not always, available. When monthly data are available a weekly attendance array is created by assuming that attendance in any month means attendance for every week (beginning Sunday) that falls in the month. When monthly data are unavailable, use the date last enrolled in school. For weeks after this date and before the current interview the respondent is not in school, while for weeks prior to this date and after the preceding interview, school attendance is uncertain. Any attendance or uncertain attendance during a calendar year leads to exclusion of youth for that calendar year from the analysis in Section 3.

The level of education is based on the question: "What is the highest grade or year of regular school that you have completed and gotten credit for?" This is for all youth in survey Round 1, and in subsequent rounds for all youth that at any time since the last interview attended or were enrolled in regular school. In addition, separate questions on attainment of high school diploma and attainment of college degree are used to increase education to 12 years (high school diploma), 16 years (bachelors degree) and 17 years (masters degree) where appropriate. A question on generalized equivalency degree (GED) is *not* used. Such youths will be assigned less than 12 years of education, unless they obtain further schooling.

A.5 *Variables and Samples Used in Section 3*

The following variables, for each individual in each calendar year or each week, are the basic data for Section 3.

Annual Earnings data:

ACE_ = Annual Computed Earnings from all jobs for which wage data is available

ACE = Annual Computed Earnings from all jobs. Constructed only if wage data is available for all jobs

ARE = Annual Reported Earnings (March CPS type question)

ARE_ = Annual Reported Earnings constructed only if ACE > 0.

Annual Work Experience data:

DAEMP = Dummy for whether employed or not at any time during year

AWW = Annual Weeks Worked

AEMPS = Number of Employers over the year

AH = Annual Hours at all jobs

AH_ = Annual Hours at all jobs for which wage data is not missing

ADMJ = Dummy for whether or not simultaneously held more than one job in any week this year

AWMJ = Annual weeks held multiple job, given held a multiple job.

Weekly Earnings and Weekly Work Experience data:

WE = Weekly earnings from all jobs this week

WH = Weekly Hours from all jobs this week.

From these basic variables, we additionally construct:

ARE/AWW = Weekly Reported Earnings

ACE/AWW = Weekly Computed Earnings

ARE/AH = Hourly Reported Earnings

ACE_/AH_ = Hourly Computed Earnings

AWMJ/AWW = Percentage of annual weeks with multiple job, given held a multiple job

WE/WH = Weekly Hourly Wage from all jobs this week.

Finally for the weekly data WE, WH and WE/WH we construct Average, Max, Min, Relative Range (RR) and Absolute Range (AR) for the weekly data WE, WH and WE/WH. These refer to Average, Max, Min, Relative Range and Absolute Range for a given individual

over the year across weeks with non-zero non-missing data. As an example consider weekly earnings:

AVE (WE) = (Sum of WE over weeks with non-zero non-missing WE and WH)/AWWP
Max (WE) = Maximum of WE over weeks with non-zero non-missing WE and WH
Min (WE) = Minimum of WE over weeks with non-zero non-missing WE and WH
RR (WE) = Ln (Max (WE)/Min (WE))
AR (WE) = Max (WE) - Min (WE).

All earnings and wage data are inflated to 1984 constant dollars by the All Items CPI for urban consumers (Economic Report to President 1989 Table B-58).

Construction of these variables is described in Sections A.2-A.4. A crucial distinction is between ACE and ACE_. Annual computed earnings from all jobs, ACE, can be constructed only if earnings data are available for all jobs held in the calendar year. Annual computed earnings from all jobs for which wage data is available, ACE_, can be constructed if earnings data are available for at least one job. The sample sizes for ACE_ will be considerably greater than those for ACE.

ACE is used for analysis of annual earnings. Since the sample for ARE, annual reported earnings, is much larger, we additionally define ARE_, annual reported earnings given ACE can be constructed, to permit comparable samples for analyzing computed and reported earnings.

ACE_ is used for analysis of hourly earnings to compute hourly computed earnings, given earnings for at least one job, we divide ACE_ by AH_, annual hours at all jobs for which wage data are available.

Regarding sample compositions used in the analysis, the empirical work in Section 3 is limited to youth age 18 years or more, not in the military and not in school at any time during the year, and with education of grade 8 or more. To ensure cell sizes of at least 30, look at:

AGE 18-19	ED 8-11, 12	Years 79-84
20-22	8-11, 12, 13-15	79-84

23–24	8–11, 12, 13–15	81–84
25–27	8–11, 12, 13–15, 16+	83–84

where

AGE = age in years at March 12 of the calendar year.

ED = highest grade of completed schooling at the end of the calendar year.

Beyond that, whenever data is available it is used. Since the number of missing observations varies by data items, this leads to many samples.

Sample sizes are given in Tables A.1–M, for men, and A.1–W, for women. For each cell, the upper three entries are for samples A, B, and C; the second three entries are for samples D, E and F; the third three entries are for samples G, H and I; and the lowest three entries are for samples J, K and L. Samples A to M are defined in Table A.2. A listing of the samples used for each of the variables in the tables in Section 3 is given in Table A.3.

The analysis of Section 3 is for all youth not in the military or in school (sample A), leading to a sample initially larger for women. This sample is used to compute the employment rate – DAEMP. Youth are dropped from the analysis only to the extent that relevant data are missing.

The primary data throughout this study are the work history data on each job held since the preceding interview. The analysis of this data in section 3 is restricted to those who worked at some stage during the year (sample B). This and subsequent samples are smaller for women than for men, except for youth with 12 years of education.

To analyze weeks worked during the year and related variables – AWW, AEMPS and ADMJ – we need to exclude youth for whom the dates of employment for any job are missing or invalid (sample C). About 2 percent of youth are excluded for this reason, mostly in 1979 due to missing data in the first survey, and more often male. Sample C is the basis for all subsequent samples but sample H.

TABLE A.1-M

SAMPLE SIZES a/,b/

GRADE	AGE	1979			1980			1981			1982			1983			1984			1979-84 ALL		
8-11	18-19	114	108	96	131	117	114	151	135	133	165	144	142	116	96	93	46	43	43	723	643	621
		96	95	86	114	113	108	133	132	129	142	141	136	93	91	92	43	42	41	621	614	590
		96	98	86	107	110	102	129	125	118	137	130	126	91	89	84	41	39	39	591	591	[illegible]
		95	55	51	101	67	60	117	75	65	125	94	82	80	63	56	30	24	20	556	372	334
	20-22	102	99	89	159	150	145	177	159	156	199	175	172	241	211	205	262	241	239	1140	1031	1012
		89	82	83	145	145	139	156	155	154	172	171	164	209	205	205	239	237	235	1112	993	982
		85	86	77	139	128	123	154	143	137	164	162	154	206	193	188	234	229	226	982	941	911
		70	58	49	125	101	85	138	123	108	159	127	119	183	166	151	222	172	164	905	746	676
	23-24							59	55	52	89	77	75	105	95	95	127	119	119	380	346	341
								52	52	50	74	74	73	95	94	91	119	119	117	340	339	311
								50	49	46	73	68	65	90	89	86	117	117	116	330	323	313
								47	40	36	66	56	49	86	70	66	114	90	89	313	256	240
	25-27													54	48	47	96	88	86	150	136	133
														47	47	45	86	86	85	133	133	130
														45	43	41	85	85	81	130	128	122
														41	32	29	82	65	63	123	97	92
12	18-19	174	173	155	177	167	164	174	173	170	164	160	158	154	142	141	87	82	82	930	897	870
		155	152	151	164	160	160	170	166	167	158	157	157	141	141	140	82	82	79	870	859	853
		150	158	141	157	155	149	165	160	159	154	153	150	138	132	131	78	77	76	842	835	805
		153	92	85	146	107	99	157	121	114	150	116	109	131	96	86	75	52	52	812	584	545
	20-22	249	246	227	342	335	326	369	359	349	390	377	371	387	378	373	360	350	346	2097	2045	1992
		227	222	219	326	323	321	349	344	345	371	376	370	372	370	367	346	346	342	1991	1962	1964
		221	226	208	319	314	302	338	338	328	366	362	357	360	352	347	336	338	333	1940	1932	1875
		209	143	136	303	249	233	327	269	255	356	280	268	348	281	264	330	238	230	1873	1460	1386
	23-24							130	128	124	213	206	203	230	218	216	259	253	253	832	805	796
								124	123	123	203	201	203	216	214	211	253	251	250	796	795	785
								121	122	119	199	194	191	206	207	203	248	245	245	774	768	752
								120	100	99	192	156	148	202	164	158	243	176	174	757	596	579
	25-27													123	118	116	233	225	225	356	343	341
														116	116	116	225	224	224	341	340	340
														114	113	111	217	216	216	331	329	327
														113	89	85	215	182	176	328	271	261
13-15	20-22	45	45	45	71	71	70	69	67	67	63	62	62	78	76	75	79	79	79	425	422	393
		40	39	40	70	69	67	66	65	64	62	62	62	75	75	72	76	76	75	392	384	384
		40	41	35	68	69	60	65	63	63	62	58	58	70	68	67	75	74	74	383	372	365
		38	28	26	67	53	52	61	49	46	57	47	45	68	50	47	74	54	53	365	281	269
	23-24							43	43	43	73	71	71	78	77	77	75	75	74	269	266	265
								43	43	43	71	70	71	77	75	75	74	74	72	265	262	261
								43	43	43	69	70	70	74	75	75	68	68	68	254	256	256
								43	37	37	68	50	49	73	51	50	68	51	47	252	189	183
	25-27													48	47	47	93	93	93	141	140	140
														47	47	47	93	93	92	140	140	139
														47	46	45	91	91	91	138	137	136
														45	41	40	91	70	70	136	111	110
16-20	23-24							33	31	30	72	68	68	68	67	67	76	74	72	249	241	237
								30	29	29	68	67	68	67	67	67	72	71	71	237	230	235
								29	27	26	66	68	67	66	67	67	70	74	72	231	236	232
								26	22	22	66	47	46	67	48	48	72	61	61	231	178	177
	25-27													59	53	52	97	95	94	151	148	146
														52	52	52	94	94	93	146	146	145
														50	53	52	92	91	90	142	144	142
														53	42	42	91	72	70	144	114	112

a/ Samples A to L are defined in appendix A.

b/ For each education-age-year grouping: upper three entries are respectively samples A, B, and C; second three entries are respectively samples D, E, and F; third three entries are respectively samples G, H and I; and lower three entries are respectively samples J, K and L.

TABLE A.1-W

SAMPLE SIZES a/,b/

GRADE	AGE	1979			1980			1981			1982			1983			1984			1979-84 ALL		
8-11	18-19	126	82	77	140	92	91	132	91	91	127	80	79	100	60	61	31	17	17	656	424	422
		76	77	64	91	91	78	91	90	86	80	80	80	61	61	59	17	17	16	416	416	383
		65	75	69	78	82	79	87	88	85	80	74	71	59	53	52	16	18	17	385	390	373
		71	38	33	79	42	38	81	58	55	71	61	53	52	42	37	16	11	10	370	252	226
	20-22	101	62	56	155	97	96	178	108	106	197	108	107	212	142	141	198	134	133	1041	651	642
		56	54	49	96	95	92	105	103	100	107	106	102	141	140	135	133	133	129	638	631	607
		50	55	47	92	86	84	99	95	93	101	98	97	135	131	129	128	122	114	605	587	564
		50	37	33	82	66	58	88	82	73	96	78	71	128	99	91	116	87	77	560	449	403
	23-24							53	30	30	95	53	51	99	47	46	123	73	72	370	203	201
								29	28	28	52	52	51	46	46	45	73	73	72	200	199	196
								28	28	26	50	48	47	45	42	42	72	69	69	195	187	184
								24	17	15	47	39	36	42	31	28	69	62	59	182	149	138
	25-27													51	23	23	91	52	52	142	77	77
														23	23	23	52	52	49	75	75	72
														23	22	21	49	49	45	72	71	66
														21	19	18	44	41	37	65	60	55
12	18-19	212	193	177	243	220	218	251	232	226	217	193	192	196	173	172	82	72	72	1201	1084	1060
		176	174	172	218	218	217	227	227	227	192	192	189	172	172	169	72	72	72	1059	1055	1039
		172	181	166	210	209	205	226	219	214	184	184	183	166	161	154	72	71	71	1030	1025	998
		175	113	107	205	148	136	218	176	169	182	134	127	159	122	114	71	54	53	1010	747	708
	20-22	287	240	226	414	346	339	477	356	349	464	390	380	475	401	401	478	409	404	2545	2143	2110
		226	216	212	343	340	330	349	349	345	382	382	377	401	401	396	406	405	396	2107	2093	2058
		217	225	207	329	322	315	342	334	326	375	373	360	391	386	382	392	399	393	2046	2039	1983
		209	157	143	313	255	237	330	277	260	364	311	293	380	319	307	393	301	294	1989	1620	1532
	23-24							160	133	133	268	216	214	272	213	212	294	237	235	994	800	797
								133	132	131	215	212	209	212	212	211	235	235	229	795	791	780
								129	129	129	205	200	198	208	204	200	226	230	226	768	763	753
								120	103	101	196	164	152	198	157	147	226	187	182	748	611	582
	25-27													160	125	125	282	218	218	442	343	343
														125	125	123	218	218	214	343	343	337
														122	120	120	211	208	206	333	328	326
														119	87	83	206	171	164	325	258	247
13-15	20-22	77	73	65	130	120	118	133	123	121	126	115	113	113	103	103	112	101	99	691	635	623
		65	62	64	118	118	116	120	120	118	112	110	109	103	103	103	100	100	99	618	613	609
		63	67	60	113	114	111	116	111	110	107	110	109	101	102	102	97	101	100	597	605	592
		64	48	45	111	77	73	110	91	85	107	85	82	102	70	69	100	64	64	594	435	418
	23-24							69	63	63	106	98	98	123	110	110	109	101	101	407	373	371
								62	62	61	98	97	96	109	109	107	99	99	99	368	367	363
								60	60	60	93	93	93	105	104	103	95	97	95	353	354	351
								59	47	46	92	83	81	102	82	76	96	76	74	349	288	277
	25-27													66	56	56	126	114	113	192	170	170
														56	54	56	114	112	112	160	166	168
														56	53	52	110	109	109	166	162	161
														50	42	41	107	83	79	157	125	120
16-20	23-24							42	41	41	65	64	64	84	82	82	104	102	102	295	289	289
								41	41	41	64	64	63	82	82	82	102	102	102	289	289	288
								41	37	37	60	63	62	80	81	80	101	102	102	282	283	281
								37	27	24	62	50	49	80	53	51	102	81	91	281	211	205
	25-27													53	50	50	91	84	83	144	134	134
														50	50	50	83	83	82	133	133	132
														48	48	48	80	82	80	128	130	128
														41	36	35	80	59	58	128	95	93

a/ Samples A to L are defined in appendix A.
b/ For each education-age-year grouping: upper three entries are respectively samples A, B, and C; second three entries are respectively samples D, E, and F; third three entries are respectively samples G, H and I; and lower three entries are respectively samples J, K and L.

Table A.2

Definitions of Samples

A: Persons not in military and not in school this year AGE >= 18 and ED >= 8.

B: Sample A less those who did not work at any time in the year. It is assumed that those who had jobs since the last survey, but for whom even the dates of employment are bad or missing, did work during the calendar year.

C: Sample B less those who did work but had missing or invalid dates for one or more jobs. This is the reference sample for all the analysis, except that of Annual Reported Earnings which does not require job dates.

D: Sample C less those for whom weekly hours (hours on all jobs held in each week) are not available for even one week of the year.

E: Sample C less those for whom hours are missing for one or more jobs held during the year.

F: Sample C less those for whom the hourly wage rate cannot be constructed for even one job held during the year.

G: Sample C less those for whom hourly wage each week and weekly earnings are not available for even one week of the year.

H: Sample A less those for whom annual reported earnings are zero or missing.

I: Sample H less those for whom annual weeks worked are missing or zero. (The intersection of samples H and C).

J: Sample H less those for whom annual hours worked are missing or zero. (The intersection of samples H and E).

K: Sample C less those for whom the wage rate is missing on one or more jobs held during the year.

L: Sample K less those for whom annual reported earnings are zero or missing. (The intersection of samples H and K).

Table A.3

Samples used for Tables 3.1–3.6

Table	Variable	Sample	Name
3.1	ARE	H	Annual Reported Earnings
	ARE_	L	Annual Reported Earnings constructed only if ACE >= 0
	ACE	K	Annual Computed Earnings
3.2	Log(ARE_)	L	Log Annual Reported Earnings if ACE >= 0
	Log(ACE)	L	Annual Computed Earnings
3.3	ARE/AWW	I	Weekly Reported Earnings
	ACE/AWW	K	Weekly Computed Earnings
	AVE(WE)	G	Average Weekly Earnings
	AR(WE)	G	Absolute Range of Weekly Earnings
	RR(WE)	G	Relative Range of Weekly Earnings
3.4	ARE/AH	J	Hourly Reported Earnings
	ACE_/AH_	F	Hourly Computed Earnings
	AVE(WE/WH)	G	Average Hourly Earnings per week
	RR(WE/WH)	G	Relative Range of Hourly Earnings per week
	AR(WE/WH)	G	Absolute Range of Hourly Earnings per week
3.5	DAEMP	A	Employed during year
	AWW	C	Weeks worked in 52 week year
	AEMPS	C	Number of Employers over the year
	ADMJ	C	Dummy for simultaneous job holder
	AWMJ	M	Number of Weeks with multiple jobs
	AWMJ/AWW	M	Fraction of weeks worked with multiple jobs
3.6	AH	E	Annual Hours
	AH_	E	Annual Hours with non-missing pay
	AVE(WH)	D	Average Weekly Hours
	RR(WH)	D	Relative Range of Weekly Hours
	AR(WH)	D	Absolute Range of Weekly Hours

To investigate variation in weekly hours within the year - AVE(WH), RR(WH) and AR(WH) – weekly hours are required for at least one week (and for all jobs in that week) in the year (sample D). Less than 0.25 percent of observations are lost for this reason.

For total hours worked over the year, – AH and AH_ – we exclude from sample C youth for whom hours worked at any job are missing (sample E). About 1 percent of sample C is lost due to missing hours data, primarily in 1979. AH_ is the sum of hours at jobs for which earnings are known, while AH is the sum of hours at all jobs, regardless of whether earnings are known.

Hourly computed earnings – ACE_/AH_ – requires data for both ACE_ and AH_ (sample F). Thus earnings are needed for at least one job during the year and hours are needed for the jobs used in constructing ACE. Almost 3 percent of sample C is lost.

To investigate variation in weekly earnings within the year – AVE(WE), RR(WE) and AR(WE) – and hourly earnings across weeks within the year – AVE(WE/WH), RR(WE/WH) and AR(WE/WH) – we require both weekly earnings and hourly earnings for at least one week in the year (sample F). Almost 3 percent of sample C is lost. (Note that since earnings may be reported as hourly, weekly, monthly, ... there are some cases when weekly earnings are missing but hourly are not, and vice-versa, but for simplicity we have required that both be known). For youth who hold more than one job in any week of the year, AVE(WE/WH) will differ from ACE_/AH_.

In addition to the earnings data from the work history, data on calendar year reported earnings – ARE – are separately available (sample H). Reporting error aside, sample H should be roughly sample B less youth with missing reported earnings. Sample H is about 6 percent smaller than sample B, and is of size comparable to samples F and G which essentially require earnings and hours data for at least one job held during the year.

To compute weekly reported earnings – ARE/AWW – requires data on both ARE and AWW (sample I). This is the intersection of samples C and H. The requirement that job dates be known leads to a loss of 2 percent of sample H (similarly about 2 percent of sample B is lost for this reason).

To compute hourly reported earnings – ARE/AH – requires data on both ARE and AH

(sample J). This is the intersection of samples H and E. The requirement that annual hours be known leads to a loss of about 1 percent of sample I.

To compute annual computed earnings at all jobs - ACE - requires earnings data for all jobs held in the year (sample K). This is much more stringent than data required for ACE_ which requires earnings for just one job in the year. Tables A.1 indicate a significant decrease in sample size.

Because so many youth have incomplete earnings data, the samples for ACE and ARE are not necessarily comparable. A better comparison is obtained by restricting analysis to annual reported earnings given complete earnings data, ARE_ (sample L).

Finally, in investigating multiple job holdings, AWMJ and AWMJ/AWW, attention is restricted to multiple job holders (sample M). Sample sizes are not reported in Tables A.1 since most cells are very small. Sample sizes across all years can be obtained by multiplying sample sizes for sample C by ADMJ reported in Table 3.5.

The basic samples are sample A, the universe of respondents for Section 3; sample C, respondents who were employed during the year and for whom the dates of employment are not missing or invalid (e.g. start date after stop date); sample H, those who reported earnings during the year and for whom this data is not missing; and sample K, those for whom wage data is available on all jobs held during the year. Sample K (and L) is considerably smaller than the others, because the wage rate is not asked for jobs of less than 20 hours and/or less than 9 weeks, unless the job is the main job at the time of the survey or a government-sponsored job.

A.6 *Imputation of Missing Earnings*

Summing over all years and age-education groups in Tables A.1, sample C has 7,285 observations for men and 7,237 observations for women, while sample K has only 5,261 observations for men and 5,298 observations for women. In any one calendar year, therefore, earnings on some jobs are missing for over a quarter of youth who work during the year. For the analysis of unemployment insurance, which requires a complete time series of earnings from 1979 or the last date of school attendance, well over half the potential sample will be lost due to missing earnings.

Since most of the jobs with missing wages are less important intermittent jobs, of less than 9 weeks duration and/or less than 20 hours per week, it seems reasonable to try to impute some of these missing wages.

Recalling that hours data are available even if the wage is missing, an obvious procedure is to assign the difference between annual reported earnings and annual computed earnings for those jobs where wage data is available to hours worked at jobs with missing wages, i.e. the imputed hourly wage is (ARE-ACE_/(AH-AH_). A weakness of this approach is that measurement errors in ARE and ACE_ are greatly magnified if wages are missing for only a small fraction of hours worked, which is often the case. For example, measurement error leading to ACE_ greater than ARE leads to a negative imputed wage.

Other sources of information are instead used. The imputed hourly wage is sequentially calculated as:

(1) hourly wage for a job with the same employer reported in the preceding or subsequent interview (appropriately deflated or inflated)

(2) average hourly earnings at other jobs with known earnings this survey round, provided these jobs account for more than 50% of total hours at jobs this interview

(3) average hourly earnings at other jobs with known wages in the preceding or subsequent interview (appropriately deflated or inflated), provided these jobs account for more than 80% of total hours at jobs that interview.

Source (2) is used only if (1) is unavailable, and (3) is used only if (1) and (2) are unavailable. The inflation factors for (1) and (3) are the average wage growth for the sample, 23.0% (from surveys 1 to 2), 15.3% (2 to 3), 13.4% (3 to 4), 9.5% (4 to 5), 9.5% (5 to 6) and 11.6% (6 to 7). If data from both the preceding and subsequent surveys are available to construct (1) or (3), their average is used.

The imputed hourly wage is multiplied by actual hours per week to impute earnings per week at the job. Then weekly earnings are constructed by summing over actual or imputed earnings per week at all jobs held in the week.

This use of imputed earnings greatly increases the sample size for the analysis of unemployment insurance. Nonetheless, other criteria such as interview in all years lead to a

sample considerably smaller than the potential 6,111. It should also be clear that the sample for Section 4 onwards, which uses a work history over many years, differs from the samples for Section 3, which are for separate analyses of each calendar year.

Appendix B

This appendix provides a description of the procedures used in the construction of the data set analyzed in Sections 4 through 10. An assessment of the reliability and accuracy of our imputed measures of UI entitlements is also presented here.

B.1 *Sample Selection*

To obtain reasonably reliable measures of weekly earnings a stringent sample selection procedure was used to obtain a subsample of youths from the nationally-representative component of the YNLS. A youth had to satisfy 6 conditions to be included in the subsample. First, to minimize the biases that can arise from mistakes in recalling events further in the past a youth must have been interviewed in each of the first 7 years of the survey. Second, he or she must have worked at least once after January 1979. Third, to assure reliable measures of time employed and nonemployed an individual was required to report valid beginning and ending dates for time periods spent working, between jobs and in the military. Fourth, he or she must have left school and not returned prior to the January 1985 interview date. Fifth, a youth must have a reasonably accurate and complete time series of either reported or imputed weekly earnings beginning in January 1978 or the last date of school attendance. Finally, the respondent must have started a nonemployment spell after March 1979 or the last date of school attendance.

Table B.1 provides a summary of the number of youths affected by each of the successive screens. The resulting subsample of 3,028 individuals from the 6,111 youths in the nationally-representative component of the YNLS is used for all of the empirical analyses in Sections 4 through 10.

B.2 *Imputation of UI Entitlements*

The detailed work histories available in the YNLS provide a unique opportunity to construct accurate measures of the amount of UI benefits available to nonemployed youths. Every State determines an individual's eligibility to receive UI and the amount of benefits he or she is entitled to collect on the basis of the reason for leaving the latest employer and a detailed earnings history over a recent 52 week period, termed the "base period." While there

TABLE B.1

Effect of Sample Selection Criteria on Sample Size

Screen	Number Eliminated	Number Remaining
Nationally-Representative Sample of YNLS		6111
Missed Interview	711	5400
Never Worked	185	5215
Invalid Dates	982	4233
In School	745	3488
Incomplete Weekly Earnings History	321	3167
Always Employed	139	3028

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is variation across States in the specific earnings history collected and the definition of the base period, the complete time series of weekly earnings available from the YNLS is sufficient to calculate all of the earnings measures used by States to determine UI entitlements.

To establish whether a youth was disqualified from receiving UI because of the reason for separation from his or her last employer, we utilized the self-reported reason for the initiation of a nonemployment spell. Respondents were provided a wide array of possible causes for starting a period of nonemployment. We have condensed this range of responses into 8 reasons for the beginning of a period not working. Briefly, these 8 causes are: (1) on layoff; (2) discharged; (3) quit for other than family or health reasons; (4) quit to join the armed forces; (5) quit for family or health reasons; (6) quit to attend school; (7) on strike; (8) unknown or other reasons. Approximately 25 percent of the nonemployment spells began because of a layoff, another 10 percent resulted from discharges and 20 percent started after a quit for other than family or health reasons. Quits for family or health reasons and other reasons account for almost all of the remaining spells.

All States have disqualification provisions for voluntarily leaving work without good cause, discharge for misconduct[38] and direct involvement in a labor dispute. While the majority of State statutes do not directly specify what constitutes "good cause," most States operationally define this provision to include only causes involving the fault of the employer or other employment related reasons. As noted in Section 4, to determine the sensitivity of our results to different interpretations of the voluntary separation provision we have adopted two methods to determine eligibility based upon reason of separation. The narrow definition of eligibility disqualifies individuals unless they were on layoff or were discharged. The broad concept of eligibility disqualifies a youth if he or she reported the nonemployment spell started because of causes 5, 6, 7 or 8 listed above. This broad interpretation of the voluntary separation provision is used in all of the analyses in Sections 5 through 10.

In addition to satisfying the separation from work condition, an out-of-work individual must also demonstrate a "permanent attachment" to the labor force by attaining either a minimum level of earnings or a minimum number of weeks of work in covered employment,

[38] Our eligibility imputation procedure does not account for the misconduct provision because we are unable to distinguish between discharges for misconduct and other discharges.

or possibly both during the base period. As a result of the Federal Unemployment Tax Act virtually all employment has been covered by the UI system since 1977. The major exclusions to coverage are self-employed individuals, agricultural workers, paid participants in a government financed training program, employees of immediate family members, and certain officers of private corporations. Thus, in constructing the time series of weekly earnings in covered employment we excluded self-employment income, income from a family farm or business, income from government sponsored training programs and earnings from jobs where a youth reported his or her occupation as a farmer or farm laborer.

In conjunction with the laws of each State, the information on the reason for the initiation of a nonemployment spell and the constructed weekly time series of earnings in covered employment enabled us to impute both UI eligibility and the amount of benefits available to a youth at the beginning of each spell of nonemployment. The accuracy of these imputed measures of eligibility and UI entitlements is the subject of the last section of this appendix.

B.3 *Construction of Work History Variables*

All States use some combination of average weekly earnings throughout the base period (*AWE*), highest earnings during any calendar quarter of the base period (*HQE*) and total earnings over the base period (*BPE*) to determine an individual's eligibility to collect UI as well as the amount of benefits available during the subsequent benefit year.[39] The specific rules and regulations determining eligibility and entitlements vary from State to State and involve complex interactions between the various earnings measures above. In addition, upper and lower thresholds in both the weekly benefit amount (*WBA*) and the number of weeks of eligibility (*WE*) introduce further nonlinearities into the relationship between entitlements and an individual's work history.

To account for the interactions and nonlinearities relating program rules and the three earnings measures, we have constructed a set of dummy variables that indicate which of a series of brackets contain the combination of *AWE*, *HQE* and *BPE* associated with a youth at the beginning of a nonemployment spell. As illustrated in Table B.2 each earnings

[39] As previously noted, programs that utilise information on weeks worked (*WW*) are combining information on *AWE* and *BPE* since $WW = BPE/AWE$.

TABLE B.2

Bracket Definitions for AWE, HQE and BPE

Bracket	Earnings Measure		
	AWE	HQE	BPE
1	$0.00-$99.99	$0.00-$999.99	$0.00-$1499.99
2	$100.00-$149.99	$1000.00-$1999.99	$1500.00-$3999.99
3	$150.00-$199.99	$2000.00-$3499.99	$4000.00-$7999.99
4	$200.00-$299.99	$3500.00-$5499.99	$8000.00-$14999.99
5	$300.00 +	$5500.00 +	$15000.00 +

measure was divided into 5 brackets. The endpoints of each bracket correspond to the lower and upper thresholds determining UI eligibility and entitlements for the various earning measures. Clearly, it was not possible to account for all of the complexities involved without resulting in an unacceptably small number of spells associated with individuals in any one bracket. For example, the *BPE* brackets were selected to capture the variation both across States and over time in the minimum amount of total earnings necessary to become eligible for UI, as well as the minimum level of *BPE* needed to qualify for the maximum amount of benefits available. The minimum level of *BPE* necessary to qualify for UI benefits varied from $150 in Hawaii in 1979 to more than $3000 in 1985. The first 2 *BPE* brackets account for this lower threshold. Similarly, the upper 3 brackets in *BPE* were chosen to allow for the nonlinearities introduced by the maximum amount of benefits payable (i.e., maximum *WBA* times the maximum *WE*) under various State programs. The minimum level of *BPE* necessary to qualify for the maximum potential benefits varied from about $4000 in Illinois in 1979 to $21,500 in Colorado in 1985.

Brackets in *HQE* and *AWE* were chosen in a manner similar to the procedure used to select the *BPE* brackets. States which base entitlements on *HQE* have upper and lower thresholds in *HQE* equivalent to the *BPE* limits discussed above. Variation in the minimum *WBA* and maximum *WBA* thresholds influenced the choice of brackets in *AWE*. Finally, the additional eligibility requirements of *BPE* greater than 1.5 times *HQE* or a weeks of work requirement also effected the selection of the lower brackets in both *HQE* and *AWE*.

The empirical specifications in Sections 7 through 9 incorporate a set of work history controls based on these bracket definitions. Let a certain combination of *BPE*, *HQE* and *AWE* describe a worker type and define a dummy variable WT_i equal to 1 if an individual is a worker of type i or 0 otherwise. The empirical results in this report are based on the definition of 22 worker types for the men and 15 worker types for the women as defined in Tables B.3–M and B.3–W respectively.

B.4 *Accuracy of Imputed Measures of UI Eligibility and Entitlements*

The self-reported measures of UI receipt available in the YNLS provide an opportunity to assess the accuracy of our imputed measures of UI eligibility and entitlements. While

TABLE B.3-M

Definition of Work History Controls for Men

Worker Type	Earnings Brackets BPE	HQE	AWE	Worker Type	Earnings Brackets BPE	HQE	AWE
WT_{m1}	1	1-2	1	WT_{m12}	3	2	2
WT_{m2}	1	1-2	2	WT_{m13}	3	2	3
WT_{m3}	1	1-2	3	WT_{m14}	3	3	3
WT_{m4}	1	1-2	4-5	WT_{m15}	3	2-3	4-5
WT_{m5}	2	1	1-2	WT_{m16}	3	4-5	4-5
WT_{m6}	2	2	1	WT_{m17}	4	3	3
WT_{m7}	2	2	2	WT_{m18}	4	3	4-5
WT_{m8}	2	1-2	3-4	WT_{m19}	4	4	4
WT_{m9}	2	3	3	WT_{m20}	4	4-5	5
WT_{m10}	2	3-4	4-5	WT_{m21}	5	4	4-5
WT_{m11}	3	2	1	WT_{m22}	5	5	5

TABLE B.3-W

Definition of Work History Controls for Women

Worker Type	Earnings Brackets BPE	HQE	AWE	Worker Type	Earnings Brackets BPE	HQE	AWE
WT_{w1}	1	1-2	1	WT_{w9}	3	2	2-4
WT_{w2}	1	1-2	2	WT_{w10}	3	3	3
WT_{w3}	1	1-2	3-5	WT_{w11}	3	3-5	4-5
WT_{w4}	2	1	1-2	WT_{w12}	4	3	3
WT_{w5}	2	2	1	WT_{w13}	4	3	4-5
WT_{w6}	2	2	2	WT_{w14}	4	4-5	4-5
WT_{w7}	2	1-4	3-5	WT_{w15}	5	4-5	4-5
WT_{w8}	3	2	1				

the data available do not permit us to identify individual spells of UI receipt, the YNLS does provide reliable calendar year measures of the total number of weeks of UI receipt, the average WBA over the year and the months in which benefits were received. Thus, the following assessments, as well as the analyses in Section 4, are based upon annual measures of eligibility and entitlements constructed from our measures imputed at the beginning of a period of nonemployment.

Calculating annual values for the imputed UI variables is straight forward for individuals who experience a single spell of nonemployment that begins and ends within a single calendar year. This exercise is also relatively simple for individuals who experience multiple nonemployment spells all occurring within a calendar year. Ambiguities arise when a nonemployment spell overlaps two calendar years, especially if a person experiences more than one period of nonemployment during a given year. When this situation arose the number of weeks of eligibility were allocated to the beginning weeks of a nonemployment spell.[40] For example, suppose a youth was eligible for 26 weeks of UI benefits at the beginning of a 30 week nonemployment spell where 18 weeks occur in one calendar year and 12 weeks take place in the second year. In this case 18 weeks of eligibility would be assigned to the first year and the remaining 8 weeks would be allotted to the second calendar year.

Table B.4 presents a cross-tablulation of our estimated eligibility to receive benefits with reported receipt of UI payments during a calendar year. The first entry in each cell represents the frequency and the second entry denotes the percent of cases in each cell. To be deemed eligible a youth must have been entitled to receive at least one week of UI benefits at some time during a calendar year. Two sets of results are presented in the table corresponding to the two definitions of eligibility described above and in Section 4. The first set of 2 columns presents the results for our broad interpretation of the voluntary separation provision and the second set refer to the narrow definition of eligibility, which assumes all quitters are ineligible.

[40] A similar problem arises in the allocation of the number of weeks of unemployment to each calendar year when a spell overlaps two years. Again, the weeks of unemployment were assumed to occur at the beginning of the nonemployment spell. While this does not impact on the accuracy assessment, it does effect the calendar year measures of eligibility and utilisation analysed in Section 4.

TABLE B.4

Frequency Table of Imputed Eligibility and UI Receipt for Both Definitions of Eligibility

(percentage of cases in each category in parentheses)

	Broad Definition		Narrow Definition	
	Ineligible	Eligible	Ineligible	Eligible
Nonrecipient	4214 (58.2)	1869 (25.8)	5134 (71.0)	949 (13.1)
UI Recipient	260 (3.6)	892 (12.3)	333 (4.6)	819 (11.3)

The results in Table B.4 are very encouraging. Using the broad definition of eligibility, an obvious error was made in only 3.6 percent of the cases: i.e., cases where a person reported receiving UI payments when we determined they were ineligible for benefits. A further examination of these 260 cases indicated that just 69 cases were judged to be ineligible because of insufficient earnings in covered employment, while the other 191 incorrect determinations resulted from the self-reported reason for beginning a nonemployment spell. Surprisingly, this type of error only occurs in 4.6 percent of the cases under the narrow interpretation of the voluntary separation provision. In addition, it is possible that erroneous eligibility imputations were made for the cases where we determined an individual was eligible for UI benefits but he or she did not report receipt of any payments. Alternatively, all 1869 or 949 cases, under the broad and narrow definitions respectively, could be the result of incomplete take-up rates for benefits.

Table B.5 presents summary statistics for the difference between reported average benefit payments and our imputed *WBA* for the years 1979 to 1984. Similar measures for the difference between weeks of receipt and the imputed value for weeks of eligibility are reported in Table B.6. In order to make the two measures used in this latter table comparable, the imputed measure for weeks of eligibility is set equal to the lesser of *WE* or the number of weeks of nonemployment during the year. The results in Tables B.5 and B.6 provide further evidence of the remarkable accuracy of our imputed measures of UI entitlements.

TABLE B.5

Summary Statistics for the Difference between Reported and Imputed WBA by Year for Broad Definition of Eligibility

Year	Lower Quartile	Median	Upper Quartile
1979	-3	1	19
1980	-8	1	17
1981	-11	1	23
1982	-11	1	21
1983	-19	0	21
1984	-11	2	29

TABLE B.6

Summary Statistics for the Difference between Reported Weeks of UI Receipt and Imputed WE Adjusted for Weeks of Nonemployment by Year for Broad Definition of Eligibility

Year	Lower Quartile	Median	Upper Quartile
1979	-3	-1	1
1980	-3	-1	3
1981	-4	-1	1
1982	-1	-2	2
1983	-2	1	8
1984	-3	-1	3

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